UNIVERSIDADE FEDERAL DO PARÁ
INSTITUTO DE TECNOLOGIA
PROGRAMA DE PÓS-GRADUAÇÃO EM ENGENHARIA ELÉTRICA

RUBENS DE ANDRADE FERNANDES

SMARTLVENERGY: UM FRAMEWORK PARA GESTÃO ENERGÉTICA INTELIGENTE E DESCENTRALIZADA DE SISTEMAS LEGADOS DE BAIXA TENSÃO

TD 14/2024

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Orientador: Professor Dr. Carlos Tavares da Costa Júnior

Coorientador: Professor Dr. Raimundo Cláudio Souza Gomes

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AUTOR: **RUBENS DE ANDRADE FERNANDES**

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”Não sabendo que era impossível, ele foi lá e fez.”

(Jean Cocteau)

RESUMO

Essencial para o progresso tecnológico e econômico, a energia elétrica requer soluções e estratégias bem fundamentadas para um gerenciamento eficiente e sustentável. Unidades consumidoras existentes, sem recursos tecnológicos modernos, necessitam de alternativas graduais para otimizar o uso de energia, aproveitando ao máximo os recursos pré-estabelecidos. Nesse contexto, o *retrofit* oferece uma atualização eficaz dessas infraestruturas. Modelos e estratégias sistemáticas podem padronizar e garantir a replicação dessas soluções em diferentes contextos através de abstrações conhecidas como *frameworks*. Contudo, há uma carência de *frameworks* para viabilizar a implantação de estratégias sistematizadas de *retrofit* para a gestão energética, especialmente no setor elétrico de baixa tensão. Para preencher essa lacuna, esta tese apresenta o *framework* SmartLVEnergy, proposto para orientar a concepção de estratégias inovadoras de *retrofit* para modernizar instalações legadas de baixa tensão com soluções de IoT, AIoT e computação distribuída, otimizando a gestão energética com recursos tecnológicos distribuídos e capacidades preditivas avançadas. Os experimentos realizados nesta tese são apresentados no formato de agregação de artigos científicos, que contribuíram para a concepção do *framework* SmartLVEnergy. Como resultado, foi possível implementar ferramentas de gestão energética em cenários prediais e industriais existentes de maneira sistematizada, fundamentada nas premissas do *framework* proposto. O enfoque principal foi a análise e previsão da demanda energética das instalações e seus respectivos circuitos, permitindo antever e mitigar eventos de ultrapassagem de demanda das unidades consumidoras, conforme as diretrizes da Agência Nacional de Energia Elétrica no Brasil. As estratégias concebidas incluíram o desenvolvimento, a utilização e a integração de recursos de sensoriamento, comunicação e computação, distribuídos localmente, na nuvem e na borda, de acordo com os preceitos do *framework* SmartLVEnergy, maximizando o aproveitamento dos recursos existentes conforme as necessidades específicas de cada instalação. O *framework* proposto é flexível e permite a integração, a expansibilidade e a interoperabilidade das soluções tecnológicas ao longo dos sistemas legados, permitindo operações conforme as peculiaridades e recursos de cada contexto pré-existente. Esta versatilidade confirma a relevância deste trabalho como uma proposta robusta e sustentável para promoção da eficiência energética na atualidade, especialmente em sistemas legados de baixa tensão.

Palavras-chave: eficiência energética; gerenciamento energético; retrofit; internet e inteligência artificial das coisas; sistemas legados de baixa tensão.

ABSTRACT

Essential for technological and economic progress, electrical energy requires well-founded solutions and strategies for efficient and sustainable management. Existing consumer units, lacking modern technological resources, need gradual alternatives to optimize energy use, making the most of pre-established resources. In this context, retrofit offers an effective update for these infrastructures. Systematic models and strategies can standardize and ensure the replication of these solutions in different contexts through abstractions known as frameworks. However, there is a lack of frameworks to enable the implementation of systematic retrofit strategies for energy management, especially in the low-voltage energy sector. To fill this gap, this thesis presents the SmartLVEnergy framework, proposed to guide the design of innovative retrofit strategies to modernize legacy low-voltage installations with IoT, AIoT, and distributed computing solutions, optimizing energy management with distributed technological resources and advanced predictive capabilities. The experiments conducted in this thesis are presented in the format of aggregated scientific articles, which contributed to the conception of the SmartLVEnergy framework. As a result, it was possible to implement energy management tools in existing building and industrial scenarios in a systematic manner, based on the premises of the proposed framework. The main focus was the analysis and prediction of the energy demand of the installations and their respective circuits, allowing to anticipate and mitigate demand overrun events of the consumer units, following the guidelines of the Brazilian National Electric Energy Agency. The strategies conceived included the development, use, and integration of sensing, communication, and computing resources, distributed locally, in the cloud, and at the edge, according to the principles of the SmartLVEnergy framework, maximizing the use of existing resources according to the specific needs of each installation. The proposed framework is flexible and allows the integration, expandability, and interoperability of technological solutions across legacy systems, enabling operations according to the peculiarities and resources of each pre-existing context. This versatility confirms the relevance of this work as a robust and sustainable proposal to promote energy efficiency today, especially in legacy low-voltage systems.

Keywords: energy efficiency; energy management; retrofit; internet and artificial intelligence of things; low-voltage legacy systems.

LISTA DE ILUSTRAÇÕES

LISTA DE ABREVIATURAS E SIGLAS

ACU	Automation and Communication Unit
AIoT	Artificial Intelligence of Things
ANEEL	Agência Nacional de Energia Elétrica
ARIMA	Autoregressive Integrated Moving Average
CAPES	Coordenação de Aperfeiçoamento de Pessoal de Nível Superior
CIN	Coupling and interaction nodes
CPU	Central Processing Unit
CSFs	Computational support functions
DRFs	Domain retrofitting functions
FPGA	Field-Programmable Gate Array
GPU	Graphics Processing Unit
GRNN	General Regression Neural Network
IAS	Industry Applications Society
IEEE	Institute of Electrical and Electronics Engineers
INDUSCON	International Conference on Industry Applications
IoT	Internet of Things
ISFs	Interdomain Support Functions
ISSN	International Standard Serial Number
JCR	Journal Citation Reports
LAN	Local Area Network
LSTM	Long Short Term Memory
MAN	Metropolitan Area Networks
ML	Machine Learning
OPs	Operational primitives

P2P	Peer-to-peer
PoI	Points of interface
PPGEE	Programa de Pós-Graduação em Engenharia Elétrica
RFR	Random Forest Regressor
SARIMA	Seasonal ARIMA
SCC	Supervision and Control Center
SmartLVEnergy	Smart Low-Voltage Energy
SmartLVGrid	Smart Low-Voltage Grids
SN	Service Node
SoC	System-on-a-Chip
SVR	Support Vector Regression
TPU	Tensor Processing Unit
UEA	Universidade do Estado do Amazonas
UFPA	Universidade Federal do Pará
WSN	Wireless Sensor Networks
XGBoost	Extreme Gradient Boosting
XGBR	XGBoost Regressor

SUMÁRIO

1 INTRODUÇÃO

A preparação desta tese segue os princípios estabelecidos na resolução n° 3359 do regimento do Programa de Pós-Graduação em Engenharia Elétrica (PPGEE) da Universidade Federal do Pará (UFPA). De acordo com o §2° do artigo 54 deste regulamento, a tese pode ser apresentada tanto no formato tradicional quanto por meio da agregação de artigos científicos.

Segundo o Artigo 54 - "Para o Doutorado, a Tese pode ser desenvolvida pelo método tradicional ou por agregação de artigos científicos".

De acordo com o §2°, a elaboração da tese por agregação de artigos científicos deve incluir pelo menos três artigos completos publicados em revista especializada com comitê editorial, cumprindo os índices mínimos de aceitação estabelecidos pelo PPGEE. Alternativamente, um capítulo de livro, livro inteiro ou patente também podem ser aceitos. Todos os documentos devem ser relevantes para o tema da tese e estar em conformidade com os critérios do Qualis da CAPES. O PPGEE definirá em resolução específica os índices mínimos de aceitação do periódico.

Segue a lista cronológica dos trabalhos aceitos e publicados que compõem a estrutura desta tese de doutorado:

1. Energies - MDPI (ISSN: 1996-1073). Qualis CAPES A2 em Engenharias IV (2017-2020), JCR: 3.0, CiteScore: 6.2. *A Retrofit Strategy for Real-Time Monitoring of Building Electrical Circuits Based on the SmartLVGrid Metamodel*.

2. Sustainability - MDPI (ISSN: 2071-1050). Qualis CAPES A2 em Engenharias IV (2017-2020), JCR: 3.3, CiteScore: 6.8. *A Demand Forecasting Strategy Based on a Retrofit Architecture for Remote Monitoring of Legacy Building Circuits*.

3. IEEE Sensors Journal - IEEE (ISSN: 1558-1748). Qualis CAPES A1 em Engenharias IV (2017-2020), JCR: 4.3, CiteScore: 7.7. *SmartLVEnergy: An AIoT Framework for Energy Management through Distributed Processing and Sensor-Actuator Integration in Legacy Low-Voltage Systems*.

Nas seções subsequentes, avançaremos com as discussões pertinentes a esta tese, abordando a contextualização e principais desafios relacionados ao tema de pesquisa, problemáticas e motivações, a hipótese de pesquisa, os objetivos e a organização deste documento de tese.

1.1 CONTEXTUALIZAÇÃO

O advento da era digital no século XXI trouxe avanços tecnológicos significativos, que se refletem em diversos setores da sociedade. Uma porção desses avanços está centrada na eficiência e na otimização dos recursos essenciais para as atividades diárias, como a energia elétrica e a água. Para isso, os paradigmas digitais deste século, como Internet das Coisas (IoT), *Smart Buildings*, *Smart Grids* e *Smart Cities*, viabilizam a transformação tecnológica nos setores residenciais, prediais, industriais e metropolitanos, garantindo o gerenciamento e controle eficiente desses recursos (Gomes *et al.*, 2019).

Apesar da transformação digital oriunda dos preceitos desses paradigmas, muitos sistemas pré-existentes tornaram-se obsoletos frente às novas tecnologias emergentes. Entretanto, eles ainda podem desempenhar papéis fundamentais nas práticas cotidianas. Esses sistemas são denominados de sistemas legados (Cao; Iansiti, 2022; Ntafalias *et al.*, 2022). Mesmo ainda funcionais, lâmpadas, tomadas, equipamentos eletrodomésticos e outros dispositivos eletroeletrônicos, quando obsoletos, passam a compor parte dos sistemas e infraestruturas legados nos setores aos quais pertencem.

O setor elétrico de baixa tensão, que ainda mantém grande parte de suas operações manuais e equipamentos desde sua concepção, consiste em muitos elementos e infraestruturas pré-existentes. No entanto, mesmo sendo composto em grande parte por recursos e atividades legadas, a presença deste setor é um forte indicador de desenvolvimento socioeconômico. Como exemplo disso, Jaiswal *et al.* (2022) e Said, Bhatti e Hunjra (2022) destacam os impactos do setor elétrico no progresso e desenvolvimento sustentável e socioeconômico. Nas análises apresentadas, os autores adotam a demanda energética como fator correlato ao desenvolvimento socioeconômico. Portanto, destaca-se a relevância de gerir adequadamente a demanda energética das unidades consumidoras com o objetivo de implementar medidas que reforcem e otimizem o uso dos insumos energéticos.

Nesse contexto, a concepção da Internet das Coisas, do inglês *Internet of Things* (IoT), possibilita a gestão de ativos e insumos essenciais por meio de soluções digitais avançadas, as quais integram sensoriamento, controle e comunicação em rede de dados. Essas soluções, quando aplicadas ao setor elétrico, permitem gerenciar remotamente a demanda energética e outras grandezas elétricas em tempo real, eliminando ou reduzindo a necessidade de intervenção humana (Tamilarasu *et al.*, 2021; Aoun *et al.*, 2021). Tal abordagem minimiza potenciais erros de medição e assegura a coleta de dados em um tempo pré-determinado.

Como um resultado da fusão entre soluções concebidas a partir dos conceitos do IoT e da aplicação de técnicas avançadas de Inteligência Artificial, surge o conceito de Inteligência Artificial (IA) das Coisas, do inglês *Artificial Intelligence of Things* (AIoT) (Gao *et al.*, 2023). Através desse paradigma, os dados recolhidos por redes de sensores sem fio (*Wireless Sensor Networks*, WSN), ou outras soluções digitais IoT, são utilizados para tarefas de Aprendizado de

Máquina, incluindo regressão, classificação e agrupamento. A partir disso, é possível viabilizar análises preditivas, para aprimorar a qualidade das decisões tomadas.

A relevância das soluções de IoT e AIoT no âmbito energético é incontestável, especialmente devido ao crescimento contínuo na demanda por energia e na necessidade em gerenciar de forma eficiente outras grandezas elétricas (Matin *et al.*, 2023). Essas tecnologias têm o potencial para transformar os sistemas elétricos de baixa tensão, impulsionando-os rumo a uma maior sustentabilidade, eficiência e resiliência. Isso inclui os setores residenciais, prediais, industriais e urbanos. Mediante a implementação de estratégias sistemáticas cuidadosamente delineadas, ajustadas às necessidades e realidades específicas das unidades consumidoras, é possível integrar soluções digitais provenientes desses paradigmas em cenários pré-existentes, mesmo naqueles com escassez de recursos tecnológicos. Dessa forma, viabiliza-se uma alternativa concreta para a convergência digital do setor elétrico pré-existente.

Nas seções subsequentes, serão abordados desafios e oportunidades associadas à modernização dos sistemas elétricos legados de baixa tensão e à implementação de soluções inteligentes neste setor.

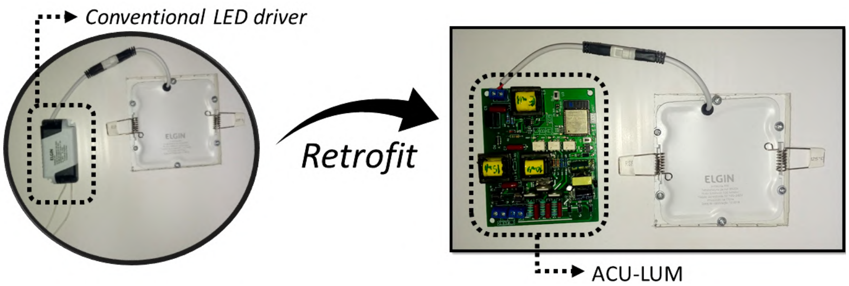
1.2 DESAFIOS NA MODERNIZAÇÃO DO SETOR ELÉTRICO

Na busca pela modernização de sistemas legados, uma prática comum envolve a substituição total ou parcial dos componentes existentes para acelerar os processos de convergência tecnológica. Contudo, essa estratégia pode levar a custos elevados e ao desperdício dos recursos usuais. Mhlanga, Denhere e Moloi (2022), por exemplo, propuseram uma alternativa para viabilizar a educação na África durante a pandemia da COVID-19 por meio da digitalização das metodologias educacionais. Eles salientaram as dificuldades da implementação rápida e abrupta deste processo de convergência em países emergentes. Portanto, para que essas nações possam implantar novos recursos tecnológicos, torna-se essencial adotar estratégias menos disruptivas e uma transição digital gradual, maximizando a utilização de recursos existentes.

Nesse contexto, surge a oportunidade de aplicar estratégias de modernização e personalização de sistemas já estabelecidos, beneficiando-se dos recursos legados existentes. Esta abordagem, também conhecida como *retrofit*, é particularmente útil para atualizar infraestruturas e sistemas que, apesar de desempenharem funções essenciais, carecem de interfaces ou capacidade de interoperabilidade com sistemas mais modernos (Nair; Verde; Olofsson, 2022; Alabid; Bennadji; Seddiki, 2022; Saffari; Beagon, 2022).

Para ilustrar essa abordagem, apresentamos em Fernandes *et al.* (2022) uma proposta sistemática para transformação digital de sistemas de iluminação legados. A fim de evitar a substituição completa dos equipamentos já em uso, optou-se por modernizar os *drivers* de iluminação LED antigos, que não possuíam recursos de controle ou monitoramento remoto. Estes foram substituídos por dispositivos capazes de monitorar tanto o consumo de energia quanto o status operacional da luminária. Além disso, esses novos dispositivos permitem acionar a lâmpada de forma remota e controlar o fluxo luminoso por meio de redes sem fio. A Figura 1 demonstra o processo de *retrofit* realizado para modernização das luminárias de LED, onde o ACU-LUM foi o hardware moderno que substituiu o *driver* de LED legado.

Figura 1. *Retrofit* para modernização de iluminação LED.



Fonte: (Fernandes *et al.*, 2022).

Perspectivas como esta tornam viável a implementação de soluções digitais de IoT e AIoT em ambientes legados (Yigitcanlar *et al.*, 2020). Contudo, a complexidade dessa implementação pode não ser uniforme, dependendo das particularidades de cada sistema ou infraestrutura. A escolha da estratégia apropriada deve considerar os recursos disponíveis e as necessidades específicas de cada setor. Como exemplo, existem estratégias que habilitam a gestão energética por meio do monitoramento remoto de circuitos elétricos, sem o uso de serviços sofisticados de processamento, comunicação e armazenamento. Este cenário é comum em comunidades indígenas, rurais e isoladas, conforme apresentado nos trabalhos de Ali *et al.* (2023a) e Kalpana *et al.* (2023). Em contraste, outras comunidades podem requerer estratégias sofisticadas e funcionalidades distintas, incluindo o monitoramento individual de cargas específicas em uma instalação, ressaltando a necessidade de abordagens personalizadas para a digitalização de grandezas elétricas e outros parâmetros desejados. Ahmad *et al.* (2024), por exemplo, propuseram um dispositivo centralizador para coleta de dados energéticos oriundos dos disjuntores do quadro principal de energia de uma instalação legada. Com esses dados, os autores utilizaram recursos de Aprendizado de Máquina para determinar, por clusterização, qual carga estaria operante a partir de sua assinatura de corrente elétrica. Esta aplicação caracteriza-se como uma solução de AIoT em uma infraestrura pré-existente.

No entanto, observa-se a necessidade de estabelecer metodologias sistematizadas, ancoradas em protocolos e normas bem definidas, com o objetivo de padronizar a execução de estratégias de *retrofit* para serem aplicadas em processos de modernização e atualização em diversos casos e sistemas. Identificam-se na literatura poucos modelos e metamodelos de referência para tal propósito, o que dificulta a concepção e implementação uniforme de estratégias voltadas à transformação digital de sistemas legados.

Nesse contexto, destaca-se o metamodelo SmartLVGrid, uma proposta inovadora para viabilizar a transição digital dos sistemas elétricos em direção ao paradigma de *Smart Grids*

(Gomes *et al.*, 2019). Esse metamodelo consiste em primitivas operacionais e pilhas de protocolos bem estabelecidos para definição e modelagem de estratégias de *retrofit* para modernização dos sistemas de distribuição de energia de baixa tensão. Em outro estudo, propusemos adaptações neste metamodelo para idealizar um modelo de sistema capaz de modernizar edifícios legados em direção ao paradigma de *Smart Buildings*, possibilitando que os protocolos e primitivas do SmartLVGrid pudessem ser utilizados em outros casos e sistemas além dos sistemas de distribuição de energia de baixa tensão (Fernandes *et al.*, 2022).

Todavia, a literatura ainda não apresentou alternativas específicas para orientar a automação e sistematização da gestão de recursos energéticos em sistemas residenciais, industriais ou prediais já existentes. Uma abordagem promissora envolve a expansão do escopo teórico das definições e modelagens propostas por metamodelos, integrando um contexto orientado à ação por meio de *frameworks* (Shehory; Sturm, 2014). Um *framework* concebido com base em estratégias de *retrofit* facilitaria o desenvolvimento e a aplicação de soluções inteligentes para gerenciamento energético em infraestruturas estabelecidas, mas ainda não otimizadas, utilizando tecnologias de comunicação em redes sem fio distribuídas de sensores e atuadores. Além disso, a proposta de um *framework* para esta finalidade oferece uma oportunidade para avançar o estado da arte na gestão energética de instalações legadas, incorporando tecnologias de tempo real com capacidades preditivas e em tempo real. Com isso, oportuniza-se a otimização do setor elétrico de baixa tensão em diferentes contextos e sistemas de maneira eficiente e sustentável, reduzindo a necessidade de grandes intervenções ou investimentos.

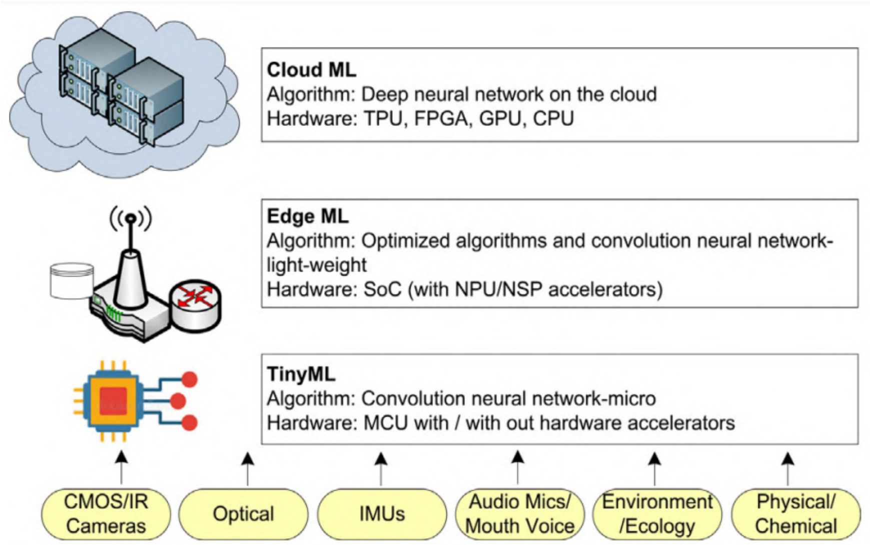
1.3 DESAFIOS NA ANÁLISE DE DADOS DOS SISTEMAS ELÉTRICOS LEGADOS

Considerando o contexto socioeconômico dos setores legados, a implementação de métodos estatísticos e soluções de Aprendizado de Máquina em infraestruturas já existentes, pode ser limitada devido aos elevados custos associados à instalação de sistemas computacionais sofisticados. Além disso, equipamentos e unidades consumidoras pré-existentes podem não dispor de recursos para aquisição de dados, ou mesmo bases de dados pré-estabelecidas para elaboração de estudos aprofundados que corroborem com processos de auditoria energética.

Nesse sentido, a implementação de soluções em nuvem para análise e processamento de dados em sistemas elétricos legados oferece diversos benefícios, contribuindo para uma gestão mais eficaz, flexível e descentralizada do consumo de energia. As soluções em nuvem fornecem um alto grau de escalabilidade, permitindo que sistemas de aquisição de dados se adaptem facilmente à expansão da infraestrutura ou ao aumento da demanda energética. Além disso, elas oferecem acesso a recursos computacionais avançados, que podem corroborar com oportunidades para a eficiência energética e favorecer a integração com outras tecnologias emergentes, como Inteligência Artificial e IoT, para aprimorar ainda mais o monitoramento e a gestão de energia (Long *et al.*, 2022).

No entanto, embora a literatura apresente trabalhos voltados ao setor elétrico que propõem o uso de aplicações específicas de Inteligência Artificial baseadas em nuvem, essa alternativa pode não ser economicamente viável para todas as comunidades, incluindo as pré-existentes (Bird *et al.*, 2022). Os custos associados ao uso intensivo e constante de serviços em nuvem, principalmente na aquisição cumulativa de parâmetros de ativos ou de unidades consumidoras, podem tornar a manutenção de soluções inteligentes financeiramente onerosa em determinados contextos. Para elucidar melhor a necessidade de recursos computacionais na implementação de sistemas inteligentes, e contextualizar os recursos de hardware necessários para aplicações específicas de inteligência artificial e análise de dados, exibe-se a Figura 2.

Figura 2. Recursos computacionais para implementação de soluções inteligentes.



Fonte: (Ray, 2022).

Conforme ilustrado, a implementação de soluções inteligentes baseadas em nuvem, ou *Cloud Computing*, exige recursos avançados de hardware, geralmente direcionados à execução de algoritmos de Aprendizado Profundo. EsSe hardware normalmente inclui unidades de processamento de tensores (TPUs), arranjos de portas programáveis em campo (FPGAs), unidades de processamento gráfico (GPUs) e unidades centrais de processamento (CPUs). Todos esses elementos possuem alta capacidade computacional em termos de processamento, memória e consumo energético, o que os torna dispositivos mais custosos de serem acessados.

Por outro lado, em aplicações inteligentes na borda (*Edge Computing*), os algoritmos de Aprendizado de Máquina (*Machine Learning*, ML) requerem processos de otimização para que possam ser embarcados em dispositivos com menor capacidade computacional, como *smartphones*, dispositivos móveis e computadores modulares. Estes últimos contam com unidades de processamento conhecidas como *System-on-a-Chip* (SoC), que condensam todos os periféricos necessários, incluindo memória e CPU, em um único semicondutor (Chandrasekaran *et al.*, 2022). Dado que esses dispositivos são geralmente alimentados por baterias, sua capacidade de processamento é intencionalmente reduzida para aumentar a autonomia.

Geralmente, aplicações robustas de modelos de IA, requerem um volume substancial de dados. Neste contexto, as soluções de AIoT oferecem capacidade de comunicação em redes de dados para o envio de informações pertinentes, além de recursos extras para análises estatísticas e preditivas desses dados, incluindo a predição e a previsão de grandezas elétricas. Dependendo dos recursos disponíveis para análise de parâmetros energéticos, estas soluções podem ser aplicadas tanto em ambientes de nuvem, quanto na borda no contexto das instalações legadas, o que agrega valor em processos de otimização energética.

No entanto, dependendo do tamanho da amostra desejada e do volume de informações, os dispositivos de sensoriamento podem consumir uma quantidade considerável de energia e largura de banda da rede na transmissão dos dados adquiridos (Schizas *et al.*, 2022). É importante enfatizar que os recursos de infraestrutura de redes de comunicação podem ser limitados em sistemas pré-existentes e, para promover processos de comunicação nestas circunstâncias, deve-se viabilizar a implantação das melhores topologias de rede para cada caso. Ademais, o envio massivo de dados para um servidor local ou em nuvem atribui uma capacidade centralizadora aos dispositivos que processam e recebem esses dados.

Em conformidade com os princípios dos sistemas distribuídos, nos quais a capacidade computacional é partilhada para minimizar dependências e problemas com sistemas centralizados, seria proveitoso que os algoritmos de aprendizado operassem diretamente nos sensores no contexto de AIoT (Hou *et al.*, 2023). Isso viabilizaria predições e classificações em tempo real de maneira distribuída nos setores energéticos, considerando que esses dispositivos, equipados com câmeras, elementos ópticos, unidades de medição inercial (IMUs), microfones e outros sensores ambientais, físicos e químicos, podem estar dispersos em um determinado ambiente. Além disso, otimizaria o custo com recursos adicionais para processamento e comunicação em redes de dados, possibilitando inferências de previsões em tempo real.

De acordo com o exposto na Figura 2, a tendência para estes cenários é a adoção do paradigma de TinyML (*Tiny Machine Learning*), voltado para soluções preditivas operáveis em plataformas microcontroladas (MCUS) de baixo custo, com capacidade reduzida de processamento e armazenamento e associada com elementos sensores (Ray, 2022). Este campo de atuação é recente e conta com fortes pesquisas para aplicações de redes neurais convolucionais em modelos extremamente compactos e precisos, como por exemplo, a arquitetura "Bacalhau-Net"descrita por Rosa *et al.* (2022), empregada para classificação de modulações de rádio.

É relevante destacar que o uso de modelos preditivos em microcontroladores requer processos rigorosos para otimizar e compactar os modelos, tais como a quantização e a destilação de conhecimento. A quantização simplifica os pesos e parâmetros das redes neurais, enquanto a destilação de conhecimento reduz a complexidade do modelo, incluindo a remoção de conexões neurais internas, com o intuito de diminuir o custo computacional (Garbay *et al.*, 2022). Embora essas estratégias sejam eficazes para implementar modelos inteligentes em plataformas microcontroladas, elas podem resultar em uma perda de precisão e acurácia, o que agrega ainda mais desafios para estudos neste campo de pesquisa (Rostami *et al.*, 2024).

Por outro lado, a literatura carece de trabalhos relacionados voltados para soluções de TinyML no setor elétrico para predições energéticas por meio de redes de sensores. Houveram notáveis exceções na previsão de energia fotovoltaica, demonstrando sua viabilidade nos microcontroladores STM32F3 e ESP32-S3 nos trabalhos de Gruosso e Gajani (2022) e Hayajneh *et al.* (2024), respectivamente. No entanto, ainda não foram obtidos trabalhos nesse âmbito aplicáveis diretamente ao gerenciamento energético considerando a realidade de unidades consumidoras inseridas no setor elétrico brasileiro ou outros cenários pré-existentes.

1.4 DISCUSSÃO DO PROBLEMA E MOTIVAÇÕES

No setor energético, soluções baseadas em IoT têm o potencial de automatizar processos de auditoria, permitindo o acompanhamento e o controle remoto de parâmetros elétricos de interesse em unidades consumidoras. Utilizando dados coletados por redes de dados acessíveis, modelos de Aprendizado de Máquina podem prever o consumo e a demanda de energia, viabilizando a otimização no planejamento e alocação de recursos energéticos. No entanto, mesmo com tecnologias avançadas disponíveis, o principal desafio abordado neste trabalho é a falta de propostas para implementar essas tecnologias em instalações existentes, especialmente aquelas com recursos limitados para processamento computacional, monitoramento e controle remoto.

No Brasil, unidades consumidoras que recebem alimentação em média e alta tensão são tarifadas de forma binômica, com base no consumo e em uma demanda energética previamente contratada com a distribuidora local (Rodrigues; Moraes; Berejuck, 2021). A demanda é avaliada a cada 15 minutos e, se ultrapassada, pode resultar em multas, conforme a Resolução Normativa ANEEL N° 1000/2021 (Agência Nacional de Energia Elétrica, 2021). Ferramentas de previsão de demanda energética para os próximos 15 minutos, baseadas em dados de monitoramento dos circuitos de baixa tensão, poderiam prever excessos e permitir ações preventivas, reduzindo o ônus financeiro aos consumidores de instalações residenciais, industriais e prediais pré-existentes e, dessa forma, colaborando para o planejamento do fornecimento energético pelas concessionárias. Apesar disso, conforme mencionado anteriormente na Seção 1.2, a literatura carece de alternativas sistemáticas para implementar esses recursos nos sistemas elétricos pré-existentes, para corroborar com o planejamento e a otimização energética.

Nesse cenário, estratégias de *retrofit* poderiam ser utilizadas para automatizar os sistemas pré-existentes com recursos computacionais, de controle e monitoramento remoto, preservando suas infraestruturas. Para que essas estratégias fossem replicáveis, a padronização das técnicas aplicáveis deveria ser sistematizada por meio de protocolos estabelecidos em um modelo de referência, que incluísse a estratégia de *retrofit* em sua concepção. Isso viabilizaria a modernização tecnológica das infraestruturas legadas e a melhoria dos processos de gerenciamento energético, promovendo sustentabilidade e eficiência energética.

O metamodelo SmartLVGrid, apesar de apoiar características semelhantes, não contempla estratégias para gestão energética analítica ou preditiva, nem metodologias para implementação de soluções de sensoriamento, controle e processamento computacional distribuído aplicáveis a este cenário. Nenhum modelo de referência no estado da arte e da técnica foi encontrado com o objetivo de promover a atualização tecnológica de sistemas energéticos legados, nem casos similares aplicáveis a instalações prediais ou fabris existentes no Brasil ou em outras localidades emergentes tecnologicamente.

Portanto, destaca-se a necessidade de evoluir esse metamodelo para um *framework*, no qual os conceitos e premissas do SmartLVGrid sejam utilizados sistematicamente no desenvolvimento e aplicação de soluções para modernização de infraestruturas legadas. Isso permitirá uma análise enriquecida dessas infraestruturas por meio do monitoramento, controle e análise preditiva das unidades consumidoras e seus respectivos circuitos, aprimorando os processos de gestão energética. Isso inclui distribuir os custos computacionais entre elementos sensores e servidores, considerando os recursos existentes e a infraestrutura de rede de dados disponível. Não foi encontrado nenhum *framework* na literatura, que seja baseado em técnicas de *retrofit*, conceitos de IoT, AIoT, ou TinyML, e que inclua a concepção de soluções inteligentes computacionalmente distribuídas em borda, nuvem, nevoa, ou localmente, aplicáveis a diferentes cenários no setor elétrico de baixa tensão.

1.5 HIPÓTESE

É possível conceber um *framework* que viabilize a criação de estratégias padronizadas e sistematizadas para a modernização tecnológica de sistemas legados de diferentes naturezas no setor elétrico de baixa tensão. A premissa é aproveitar ao máximo os recursos existentes, facilitando a gestão energética de infraestruturas com limitação de recursos, por meio de soluções desenvolvidas para promover a automação, comunicação e o uso de recursos computacionais distribuídos, conforme as necessidades das infraestruturas. Dessa forma, espera-se equiparar tecnologicamente infraestruturas menos favorecidas com infraestruturas de ponta, por meio de uma transição digital gradual com mínimos impactos socioeconômicos e estruturais, além de viabilizar a gestão de energia de forma eficiente e sustentável pelo lado da demanda.

1.6 OBJETIVOS

O objetivo desta tese é conceber e validar o *framework* denominado SmartLVEnergy, para modernizar e viabilizar o gerenciamento energético de sistemas elétricos legados de baixa tensão e orientar a implantação, o desenvolvimento e a integração de soluções de IoT, AIoT e computação distribuída por meio de estratégias sistemáticas de *retrofit*, evoluindo e expandindo a aplicabilidade do metamodelo SmartLVGrid. Com isso, almeja-se otimizar e modernizar a gestão energética pelo lado da demanda, em baixa tensão, integrando recursos preditivos, de monitoramento e de controle remoto, e processamento computacional distribuído, aproveitando ao máximo os recursos existentes em unidades consumidoras industriais, prediais e residenciais.

Os objetivos específicos desta tese são listados a seguir:

- Orientar o desenvolvimento, o uso e a integração de plataformas de *retrofit* para sensoriamento e controle energético nos cenários existentes por meio de estratégias sistemáticas, aproveitando ao máximo os recursos do legado.
- Assegurar que a interoperabilidade e os recursos de comunicação utilizados preservem as redes de dados existentes, ou que se adaptem às necessidades das instalações legadas.
- Promover a integração de recursos computacionais descentralizados para processamento, armazenamento e análise preditiva de dados energéticos, distribuídos em borda, névoa, nuvem, ou localmente, conforme as necessidades e recursos das instalações existentes.
- Propor um *framework* para gestão energética inteligente, fundamentado no metamodelo SmartLVGrid, para elaborar estratégias sistemáticas para implantação de soluções tecnológicas que modernizem infraestruturas legadas de baixa tensão e preservem ao máximo os recursos existentes.

1.7 ORGANIZAÇÃO DO DOCUMENTO DE TESE

A partir deste capítulo, este documento de tese está estruturado na seguinte sequência:

- No **Capítulo 2**, serão expostos os conceitos e os trabalhos relacionados que precedem este trabalho de tese, destacando as lacunas de pesquisa identificadas e as definições do *framework* proposto.
- No **Capítulo 3**, serão exibidas as contribuições de cada artigo publicado para atingir os objetivos estabelecidos. Também serão reproduzidos na íntegra os respectivos artigos que apresentam as experimentações realizadas, os resultados obtidos para validação da proposta e as perspectivas futuras de cada pesquisa conduzida.
- No **Capítulo 4**, abordam-se as conclusões do trabalho a partir dos resultados obtidos, as limitações da pesquisa e as perspectivas para trabalhos futuros a partir desta tese.

No Apêndice A, fez-se referência as publicações aceitas para o 15th IEEE/IAS International Conference on Industry Applications (INDUSCON 2023) e para o Simpósio Brasileiro de Sistemas Elétricos 2023 (SBSE 2023), como contribuições parciais da pesquisa realizada ao longo do desenvolvimento da tese.

2 REVISÃO DE LITERATURA

Neste capítulo, serão apresentados os conceitos básicos de eficiência energética discutidos nas experimentações dos artigos publicados como parte desta tese, com ênfase no cenário energético brasileiro. Em seguida, serão apresentados os trabalhos relacionados ao tema desta pesquisa, subdivididos conforme os tópicos abordados nas experimentações, que incluem soluções e *frameworks* para gerenciamento energético, modernização tecnológica e recursos preditivos no setor elétrico. Também serão expostas as definições preconizadas pelo metamodelo SmartLVGrid, utilizado como base para concepção do *framework* SmartLVEnergy. Vale destacar que os artigos anexados como capítulos desta tese contêm detalhes adicionais com as respectivas análises críticas sobre o estado da arte apresentado nesta seção.

2.1 EFICIÊNCIA ENERGÉTICA

A eficiência energética refere-se à otimização do consumo de energia, alcançada pela aplicação de práticas comportamentais, econômicas e tecnológicas em sistemas e processos (Godoi, 2011). O objetivo subjacente é minimizar o uso de energia sem comprometer a quantidade ou a qualidade dos produtos e serviços produzidos, tanto no curto quanto no médio e longo prazo. Para alcançar essa otimização, é fundamental compreender a demanda energética específica de um sistema e, consequentemente, desenvolver planos eficazes para reduzir o consumo de energia progressivamente.

Para evidenciar a relevância destes parâmetros, serão discutidos os conceitos de consumo e demanda no contexto energético brasileiro, alvo das experimentações deste trabalho.

2.2 CONSUMO E DEMANDA DE ENERGIA

A quantificação do consumo de energia de uma unidade consumidora ou de um circuito individual se dá pela totalização da energia útil ou reativa utilizada ao longo de um intervalo de tempo. Em contrapartida, a demanda energética se estabelece como a média das potências exigidas pelas cargas de uma unidade consumidora, um cálculo realizado em períodos de 15 minutos, conforme o padrão adotado no Brasil (Viana *et al.*, 2012). No Brasil, existem duas categorias nas quais as unidades consumidoras são enquadradas, denominadas Grupo A e Grupo B, as quais diferem entre si quanto às características e padrões de consumo de energia (Agência Nacional de Energia Elétrica, 2021). As unidades pertencentes ao Grupo A recebem energia com tensões iguais ou superiores a 2,3 kV e são tarifadas tanto pelo consumo quanto pela demanda energética contratada (kW). Já as unidades classificadas como Grupo B são alimentadas com tensões menores que 2,3 kV e sua tarifação se dá exclusivamente pelo consumo acumulado de energia (kWh). As unidades do grupo A incluem instalações de médio e grande porte, como edifícios e indústrias. Por outro lado, instalações do grupo B incluem residências e instalações de pequeno porte.

Embora haja fornecimento energético a partir da média tensão, grande parte das unidades consumidoras opera seus ativos e cargas em baixa tensão, necessitando de recursos para adequação dos níveis de tensão para níveis próprios para consumo. Este fato motivou a proposta, considerando a oportunidade de automatizar o setor elétrico a partir dos sistemas de baixa tensão. Nesse contexto, o monitoramento e a projeção da demanda e do consumo de energia em baixa tensão tornam-se essenciais para maximizar a economia de energia. O monitoramento em tempo real permite que os gestores antecipem e atuem em situações de demanda excessiva, minimizando despesas associadas ao excedente da demanda contratada. Ademais, a aplicação de técnicas preditivas pode aprimorar ainda mais o processo decisório na gestão energética pelo lado da demanda.

2.3 TRABALHOS RELACIONADOS

Nesta seção, abordam-se os trabalhos relacionados ao gerenciamento energético em tempo real com soluções IoT e AIoT, além de estudos sobre a evolução tecnológica por meio de técnicas e recursos de *retrofit*, *middleware*, interoperabilidade, metamodelos e *frameworks* utilizados em processos de conversão tecnológica no setor elétrico.

2.3.1 Gerenciamento Energético no Paradigma de IoT

O monitoramento de energia desempenha um papel fundamental na gestão eficiente do setor elétrico, permitindo a avaliação dos parâmetros elétricos da rede, do consumo de energia e da qualidade energética. As soluções baseadas na Internet das Coisas (IoT) têm se mostrado relevantes nesse contexto, permitindo a implementação de recursos de monitoramento em tempo real e remotamente em ambientes residenciais, prediais, industriais e metropolitanos (Anand *et al.*, 2022). Além disso, o paradigma de IoT facilita a interconexão de dispositivos dedicados ao monitoramento energético e sua integração com sistemas computacionais, incluindo soluções baseadas em nuvem.

Diversos estudos têm abordado soluções em tempo real baseadas em IoT para o monitoramento de energia. Por exemplo, Sultania, Mahfoudhi e Famaey (2020) viabilizaram o monitoramento energético em tempo real por meio de dispositivos de hardware interconectados em uma rede móvel baseada em *Narrowband* IoT (NB-IoT) para aplicações de *Smart Grids*. Da mesma forma, Shivaraman *et al.* (2020) apresentaram uma solução descentralizada para monitoramento energético em tempo real a partir de dispositivos móveis. Govindarajan, Meikandasivam e Vijayakumar (2020) realizaram um estudo de avaliação de desempenho de diferentes soluções de IoT em tempo real. Por fim, Muralidhara, Hegde e Math (2020) e Tanasiev *et al.* (2021) utilizaram soluções digitais para fornecer dados de consumo de energia em tempo real aos usuários por meio de redes de dados sem fio.

2.3.2 Modernização por Técnicas de Retrofit

A abordagem de retrofit envolve a atualização de sistemas antigos ou tecnologicamente obsoletos, tornando-os atualizados e permitindo a adoção de novos recursos (Seri *et al.*, 2021). Essas técnicas são frequentemente aplicadas a estruturas de edifícios e dispositivos legados para preservá-los e atualizá-los, requerendo um conhecimento específico dos elementos e infraestruturas existentes, para garantir interfaces adequadas e a implantação segura das funcionalidades desejadas. Por exemplo, Martín-Garín *et al.* (2018) apresentaram soluções para a automação de infraestruturas legadas usando estratégias de retrofit. Lall *et al.* (2022) propuseram uma arquitetura de retrofitting para equipamentos legados, utilizando sensores externos para coleta de dados e análise em nuvem, demonstrando sua viabilidade em um ambiente de laboratório. Já o trabalho de Kumar, Srinivasan e Mani (2022) apresentou uma abordagem de retrofit para avaliar a eficácia da integração de sistemas de sensoriamento baseados em IoT em edifícios inteligentes, demonstrando sua viabilidade como ferramentas de avaliação de sustentabilidade.

2.3.3 Soluções de Middleware e de Interoperabilidade

As soluções de middleware fornecem conexões entre sistemas heterogêneos em níveis físicos ou lógicos. Por outro lado, a interoperabilidade entre esses sistemas é um dos desafios mais complexos no domínio IoT, tanto no desenvolvimento de software quanto de hardware (Zhang *et al.*, 2021; Mishra; Varma *et al.*, 2021). Em certas situações, é necessário garantir a interação entre sistemas diferentes, independentemente do protocolo de comunicação utilizado (Rahman; Hussain, 2020; Lee *et al.*, 2021). O uso de soluções de middleware e interoperabilidade facilita a escalabilidade de aplicações IoT, a conexão e interação com sistemas existentes, reduzindo a complexidade da integração de novas tecnologias.

A literatura apresenta diversos estudos que exploram a convergência tecnológica por meio de soluções de *middleware* e de interoperabilidade. Por exemplo, Araújo *et al.* (2018a) implementou um modelo de *middleware* para *Smart Grids* a partir de uma estrutura de mediação baseada na modernização de medidores antigos para monitorar parâmetros elétricos em Redes de Sensores Sem Fio (WSNs). O mesmo grupo de autores propõe uma metodologia para a interoperabilidade de medidores antigos em *Smart Grids* usando WSNs em (Araújo *et al.*, 2018b). Fortes *et al.* (2019) apresentaram um modelo de sistema para viabilizar a interoperabilidade e interconexão de dispositivos em um campus universitário, servindo como demonstração para futuras aplicações em *Smart Cities*. Além disso, Koo e Kim (2022) propuseram um *framework* de interoperabilidade, incluindo um sistema com recursos de IoT que facilita a identificação e o uso de serviços entre plataformas heterogêneas, convertendo caminhos de recursos específicos em formatos de solicitação para cada plataforma. Por fim, Ali *et al.* (2023b) propuseram um novo modelo de *middleware* para cidades inteligentes que integra IoT e *Big Data* para superar desafios como heterogeneidade de dispositivos e segurança, com sua eficácia comprovada por testes de desempenho e equilíbrio de carga.

2.3.4 Metamodelos em Sistemas Tecnológicos

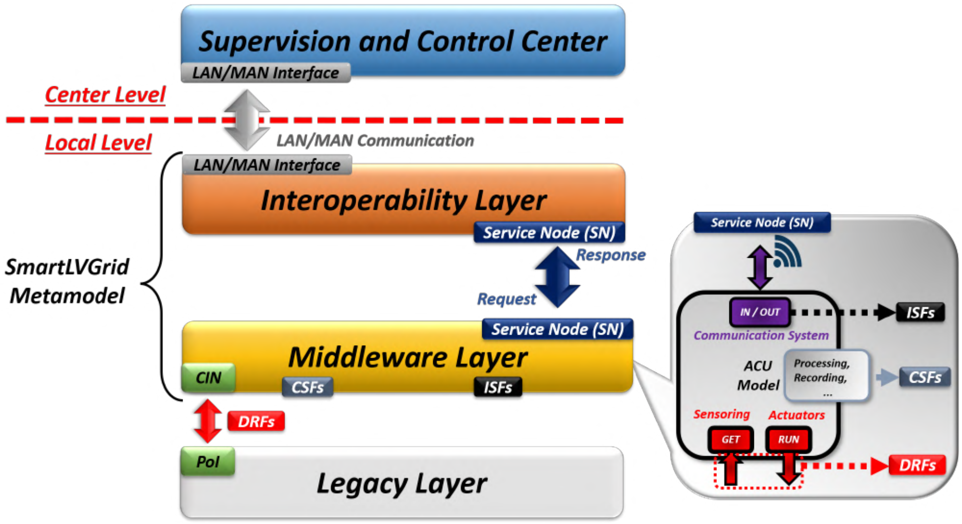
Assim como os modelos representam uma realidade, os metamodelos são utilizados para criar novas linguagens de modelagem ou expandir as existentes (Jeusfeld, 2009). Eles desempenham um papel importante na análise, criação e desenvolvimento de modelos de integração de sistemas, incluindo a integração de sistemas antigos com interfaces de mediação e interoperabilidade (Mohanty, 2015). Assim, infere-se que os metamodelos possam facilitar a transição tecnológica de sistemas pré-existentes.

Na literatura, existem estudos que relatam casos de sucesso utilizando a abordagem de metamodelos para evolução de sistemas tecnológicos. Por exemplo, Cicirelli *et al.* (2016) desenvolveram um metamodelo para a interação de dispositivos em ambientes inteligentes por meio da modelagem de relações e atributos. Hassine, Khayati e Ghezala (2017) elaboraram um metamodelo IoT, capaz de transformar soluções de *software* escritas em uma linguagem de modelagem específica para uma aplicação em Java, visando padronizar o desenvolvimento de forma orientada. Abdelouahid, Marzak e Sae (2018) também propuseram um metamodelo IoT para conectar objetos heterogêneos com alto nível de interoperabilidade. Já Gomes *et al.* (2017) introduziram um meta sistema para facilitar a transição de sistemas antigos de distribuição de energia elétrica para o paradigma de *Smart Grids*, por meio de estratégias de modernização. O metamodelo SmartLVGrid, derivado desse meta sistema, é apresentado em Gomes *et al.* (2019), fornecendo primitivas e protocolos para o uso de soluções de mediação e interoperabilidade por meio da modernização de sistemas elétricos antigos de baixa tensão. Esse metamodelo pode ser estendido a qualquer nicho tecnológico, incluindo o setor elétrico. Não foram encontradas outras abordagens similares na literatura. Portanto, o metamodelo SmartLVGrid será utilizado como alicerce para concepção do *framework* proposto, SmartLVEnergy, para a modernização de sistemas legados de baixa tensão. A seguir, serão apresentadas a definição e as características do metamodelo SmartLVGrid.

2.3.5 O metamodelo SmartLVGrid

O SmartLVGrid, ou *Smart Low Voltage Grids*, consiste de um metamodelo orientado à conversão de circuitos de baixa tensão pré-existentes para o paradigma de *Smart Grids* em sistemas de distribuição de energia legados (Gomes *et al.*, 2019). O modelo se baseia em uma série de protocolos projetados para incrementar funcionalidades de controle, supervisão e comunicação em sistemas existentes por meio de estratégias de *retrofit*. O SmartLVGrid opera tanto a nível local, próximo ao consumidor, quanto a nível central, em centros de controle de empresas de energia. A distinção geográfica desses níveis demanda o uso de interfaces de redes locais (LANs) ou metropolitanas (MANs) para estabelecer a conexão lógica entre os sistemas legados, e os centros de supervisão e controle (SCC). A estrutura de protocolos adotada pelo modelo SmartLVGrid é demonstrada na Figura 3.

Figura 3. A pilha de protocolos do metamodelo SmartLVGrid.



Fonte: (Fernandes *et al.*, 2022).

Como mostra a Figura 3, o metamodelo SmartLVGrid engloba as camadas de interoperabilidade e de *middleware*. De acordo com a estrutura de protocolos, a modernização deve ser feita na infraestrutura existente, em pontos de interface, ou *Points of Interface* (PoI), onde ocorrem as interações. A camada de *middleware* se conecta à camada legada através de um nó de acoplamento e interação, conhecido como CIN (*Coupling and Interaction Node*). Esse enlace facilita a execução de microprocessos, denominados Funções de *Retrofitting* de Domínio (DRFs), que são uma das categorias de primitivas operacionais (*Operational Primitives*, OPs) definidas pelo SmartLVGrid.

As primitivas operacionais são descritas como processos antes realizados por operadores de campo no sistema elétrico legado que passam a ser executados através dos nós de acoplamento e interação e pelos nós de serviço (*Service Nodes*, SN), unidades lógicas responsáveis pela interface entre as camadas de *middleware* e de interoperabilidade. As funções de suporte computacional (CSFs) implementam serviços de processamento e armazenamento na camada de *middleware*. Por outro lado, as funções de suporte entre domínios (ISFs) realizam os processos de comunicação na mesma camada. A seguir, serão detalhadas as camadas de *middleware* e de interoperabilidade, que compõem o metamodelo SmartLVGrid.

Localizada na base da estrutura do metamodelo, a camada de *middleware* é implementada fisicamente através de dispositivos de *retrofit*, compostos por hardware embarcado, sensores e atuadores que se adequam às DRFs a serem executadas. Esta camada também é conhecida como *Automation and Communication Unit* (ACU) e sua representação é retratada na Figura 3.

O modelo representativo do ACU conta com três portas: "In/Out", "*Get*"e "*Run*". As ISFs operam os processos e serviços de comunicação através da porta "*In/Out*"do ACU. A porta "Get"implementa a coleta de dados obtidos por meio de DRFs associadas a medições e detecção. Por último, a porta "*Run*"atua com DRFs de controle sobre a camada legada. Vale destacar que as rotinas de processamento e armazenamento de dados do ACU são implementadas pelas CSFs, juntamente com outras funções de suporte computacional.

A camada de interoperabilidade é incumbida de assegurar um conjunto de normas, hierarquias e a infraestrutura necessária para a implementação de uma rede de ACUs que interaja com estes dispositivos e aproveite suas funcionalidades. Nesta camada, cada ACU é classificado conforme sua posição na hierarquia do metamodelo SmartLVGrid. Os ACUs que supervisionam e monitoram outros ACUs e, opcionalmente, executam DRFs são chamados de coordenadores (*coordinators*). Os ACUs que executam DRFs na camada legada e são supervisionados pelos coordenadores são chamados de operadores (*operators*). Na eventualidade de expansão do sistema elétrico em operação, o que implica maior capacidade computacional do ACU coordenador, o metamodelo prevê subcoordenadores (*subcoordinators*) para cada grupo de ACUs operadores. Portanto, os subcoordenadores estarão ligados a um único ACU coordenador que se comunicará com o centro de controle para transmitir informações do sistema. É importante ressaltar, que cada ACU tem sua própria unidade de processamento, possibilitando o processamento distribuído do sistema a partir da modernização de cada ativo legado.

A seguir, apresentamos os trabalhos relacionados com previsão e predição de demanda e consumo energético com métodos estatísticos e modelos de aprendizagem de máquina, que corroboram com recursos preditivos para aprimorar o processo de tomada de decisão, o gerenciamento e o controle de carga em sistemas elétricos.

2.3.6 Previsão de Demanda Energética com Métodos Estatísticos

A previsão de demanda energética e do consumo de energia é um tema amplamente pesquisado na literatura. Os métodos estatísticos mais comumente utilizados nesse contexto são baseados em técnicas autorregressivas, sendo os mais conhecidos o *Autoregressive Integrated Moving Average* (ARIMA) e o *Seasonal* ARIMA (SARIMA). Por exemplo, os autores Zieliska-Sitkiewicz *et al.* (2021), utilizaram o método SARIMA para prever o consumo energético na Polônia em diferentes escalas de tempo. O trabalho de Velasquez *et al.* (2022), utilizou-se do método ARIMA para estimar a demanda energética no Brasil e avaliar sua previsibilidade com dados reais. Já Silva *et al.* (2022), empregaram o método SARIMA para prever o consumo de energia no setor industrial brasileiro em curto prazo. Esses métodos estatísticos permitem a previsão da demanda energética futura com base em valores passados de demanda, utilizando técnicas de reordenação dos dados presentes nos conjuntos de dados. Além disso, trabalhos como os de Shah, Jan e Ali (2022) e Manno, Martelli e Amaldi (2022) apresentaram o método de janela deslizante e modelos autorregressivos para prever a demanda energética de curto prazo.

2.3.7 Previsão de Demanda Energética com Aprendizado de Máquina

Embora os métodos estatísticos sejam eficazes na previsão de séries temporais com padrões de sazonalidade e tendência bem definidos, eles podem ser limitados quando a série temporal apresenta padrões mais complexos e não-lineares. Nesses casos, os métodos de Aprendizado de Máquina podem oferecer melhores resultados (Rajula *et al.*, 2020). Por exemplo, Shirzadi *et al.* (2021) aplicaram a regressão de Floresta Aleatória (*Random Forest Regression*, RFR) e o SVR para prever o consumo de eletricidade em médio prazo com base em um conjunto de dados do Canadá. Pavlicko, Vojteková e Blaeková (2022) propuseram modelos baseados em Redes Neurais Artificiais para prever o consumo de energia elétrica na Eslováquia. Os autores Aisyah *et al.* (2022) utilizaram modelos de Regressão de Vetor de Suporte (*Support Vector Regression*, SVR) e Regressão Generalizada (*General Regression Neural Network*, GRNN) para prever o consumo de energia na Indonésia. Arjomandi-Nezhad *et al.* (2022) relataram o uso de métodos de *Ensemble Learning*, como o regressor XGBoost (XGBR) e o RFR, para prever a demanda de energia no dia seguinte durante o período da pandemia.

Em casos de grande volume de dados, relações não-lineares, presença de ruídos e comportamentos não estacionários, as Redes Neurais Profundas podem ser uma alternativa ao Aprendizado de Máquina. No entanto, é importante ressaltar que essas redes exigem mais recursos computacionais e são mais complexas em comparação com os modelos supervisionados de Aprendizado de Máquina. É comum que os autores utilizem Redes Neurais Recorrentes, especialmente as redes LSTM, em conjunto com técnicas de janela deslizante (Elkamel *et al.*, 2020; Mustaqeem; Ishaq; Kwon, 2021; Bashir *et al.*, 2022; Torres; Martínez-álvarez; Troncoso, 2022).

2.3.8 Previsão de Demanda Energética no Contexto de Instalações Prediais

Os trabalhos mencionados anteriormente contribuem para o estado da arte da previsão de demanda e consumo energético. No entanto, esses trabalhos focaram em previsões de interesse de companhias energéticas, localidades regionais ou nacionais, não estando diretamente relacionados com instalações prediais e industriais. Portanto, buscou-se trabalhos na literatura que investigassem aplicações de previsão de demanda voltadas para instalações prediais.

Eseye *et al.* (2019) utilizaram o modelo de perceptron multicamadas para prever a demanda de edifícios residenciais, educacionais e de uso misto para as próximas 24 horas. Já Nabavi *et al.* (2021) realizaram a previsão de demanda e geração de fontes renováveis de energia elétrica (fotovoltaica e eólica) em 5 residências inteligentes. Esse estudo utilizou redes LSTM como modelos de previsão e cerca de 11 meses de dados coletados. Mounter *et al.* (2021) propuseram um estudo para auxiliar gestores e técnicos com previsões energéticas de longo prazo para um edifício da Universidade de Teesside (Reino Unido), utilizando diferentes técnicas de aprendizado de máquina, como regressão linear, SVR e redes neurais. Os autores Durand, Aguilar e R-Moreno (2022) realizaram a previsão de demanda utilizando redes LSTM aplicadas ao contexto de Smart Buildings. No trabalho de Mariano-Hernández *et al.* (2022), foram utilizados dados de consumo energético de contadores inteligentes instalados em subestações de edifícios, que registraram o consumo de todo o edifício em intervalos de 15 minutos. A partir desses dados, os autores analisaram a integração de métodos de previsão de consumo para melhorar a eficiência energética em instalações prediais. O trabalho de Lee, Kim e Gu (2023) mostrou a previsão de energia em uma empresa de alimentos com base em dados obtidos do sistema de gestão de energia da fábrica, utilizando os métodos SVR e perceptron multicamadas.

2.3.9 Soluções de AIoT para Gerenciamento Energético

Também foram selecionados alguns trabalhos que incorporam o conceito de AIoT para análise de energia elétrica, no intuito de apresentar soluções de Inteligência Artificial baseadas em dados energéticos obtidos de soluções digitais de IoT. Por exemplo, Das, Zim e Sarkar (2021) desenvolveram um sistema de controle de energia com base em um hardware que utiliza comunicação Wi-Fi, relés, sensores de corrente e armazenamento em nuvem, utilizando o algoritmo de árvore de decisão para auxiliar em tomadas de decisão quanto ao gerenciamento de consumo energético monitorado. De forma similar, Arivukkody, Gokulakannan e Kalpana (2022) apresentaram um dispositivo de hardware para monitorar a presença humana e o consumo energético em unidades consumidoras residenciais. Os autores também utilizaram um modelo de árvore de decisão sobre uma base de dados armazenada em nuvem para determinar o desperdício de energia. No trabalho de Salama e Abdellatif (2022), redes neurais foram utilizadas para prever o consumo de energia com base em dados coletados por sensores de um sistema residencial, permitindo desligar um ou mais dispositivos com o objetivo de reduzir o consumo mensal. Já Zhu, Ota e Dong (2022), implementaram uma plataforma de Inteligência Artificial para dispositivos de borda para melhorar a eficiência energética de tarefas de *edge computing* em soluções de AIoT.

2.3.10 *Frameworks* AIoT para Gerenciamento Energético

Apesar das soluções exibidas na Subseção 2.3.9, outros estudos adotam uma abordagem mais ampla através de *frameworks* voltados ao gerenciamento inteligente de energia aplicáveis em diversos setores. Estes *frameworks* orientam ações para desenvolver e implantar estratégias de gerenciamento energético com elementos sensores, atuadores, análise preditiva processamento distribuído de informações, para atender outros casos e sistemas similares.

Golpîra e Bahramara (2020) propuseram um *framework* de gerenciamento de energia aproveitando tecnologias baseadas em nuvem e IoT para redes de distribuição de energia em *Smart Cities*. Eles reduziram os custos operacionais otimizando os padrões de consumo de carga e a geração de energia alternativa com base nos preços de mercado. O trabalho de Ullah *et al.* (2021) expôs um *framework* de gerenciamento de energia para o setor industrial utilizando IoT e *Big Data* para processamento, armazenamento e visualização de dados. Essa abordagem forneceu uma metodologia flexível para que as indústrias escolham a plataforma IoT mais adequada com base em suas necessidades. Han *et al.* (2021) propuseram um *framework* de gerenciamento de energia inteligente para *Smart Grids*, residências e indústrias, incorporando soluções de dispositivos de borda para gerenciamento de energia em tempo real em comunicação com um centro de supervisão baseado em nuvem. Já Hashmi, Ali e Zafar (2021) enfatizaram a importância do gerenciamento de energia industrial ao introduzir um *framework* baseado em recursos de IoT, análise de dados e *Big Data* para adquirir dados de energia.

Outros trabalhos demonstraram abordagens práticas para validar os *frameworks* propostos utilizando soluções baseadas em sensores, comunicação e controle. Saleem *et al*. (2022), por exemplo, propuseram um *framework* para gerenciamento de energia do lado da demanda em *Smart Grids* usando recursos de IoT e Nuvem para gerar e compartilhar remotamente perfis e cargas de consumidores com empresas de energia ou consumidores. Similarmente, Ullah *et al*. (2022) implementaram uma solução de *middleware* para gerenciamento de energia do lado da demanda, focando na interoperabilidade dos recursos de monitoramento e controle de energia. Onile *et al*. (2024) apresentaram um *framework* para gerenciamento de energia, oferecendo serviços de recomendação e avaliação de consumidores e previsão de comportamento de carga para melhorar a eficiência energética. Por fim, Jha *et al*. (2024) desenvolveram um *framework* para dispositivos de gerenciamento de energia inteligente integrando recursos de software, hardware e comunicação com medidores de energia. Capacidades de previsão de demanda de energia foram incorporadas usando algoritmos de Aprendizado de Máquina

Em cenários onde o uso de elementos de sensores inteligentes para processamento de dados em tempo real é considerado, as soluções TinyML oferecem vantagens econômicas, de segurança, privacidade, largura de banda, previsão offline e latência. No entanto, nenhum dos trabalhos citados incorporaram TinyML em seus *frameworks* propostos.

2.4 LACUNAS NA LITERATURA

Embora os estudos referenciados tenham enriquecido significativamente o estado da arte e da técnica em suas respectivas áreas de interesse, identificou-se várias lacunas na literatura atual. Estas lacunas, que serão detalhadamente exploradas e abordadas no contexto deste trabalho de tese, são particularmente relevantes dado o cenário energético das unidades consumidoras pré-existentes, incluindo as que se fazem presentes no setor elétrico brasileiro. Enumeramos essas lacunas nos tópicos seguintes:

1. Inexistência de trabalhos que empreguem estratégias sistemáticas de *retrofit* para atualizar sistemas legados de baixa tensão, utilizando soluções IoT e AIoT adaptadas às necessidades das instalações, com o objetivo de otimizar a eficiência energética.

2. Escassez de metamodelos, *frameworks* ou arquiteturas genéricas para padronizar e facilitar a implementação de recursos de automação, processamento distribuído e comunicação, por meio de *retrofit*, para viabilizar a gestão de energia em sistemas elétricos legados.

3. Limitações das propostas quando aplicadas a outros casos e sistemas devido ao foco em contextos particulares e à falta de estratégias sistemáticas, dificultando a escalabilidade e

a interoperabilidade com as tecnologias emergentes.

4. Falta de propostas de soluções de *middleware* para estabelecer interfaces físicas e lógicas com sistemas legados ou recursos que facilitem a interoperabilidade de dispositivos sensores e atuadores no contexto de eficiência energética.

5. Escassez de bases de dados e de propostas para elaboração de bases de dados que registrem parâmetros energéticos de instalações pré-existentes e seus respectivos circuitos.

6. Falta de investigações que abordem sobre soluções AIoT que permitam análises energéticas preditivas a nível de circuito dentro das infraestruturas pré-existentes.

7. Falta de soluções baseadas em TinyML ou em computação em borda para análises energéticas preditivas em instalações legadas e seus respectivos circuitos.

Na próxima seção, serão expostas as premissas e definições do *framework* proposto, que contribuirá para completar as lacunas identificadas no estado da arte atual.

2.5 O FRAMEWORK SMARTLVENERGY

Para preencher as lacunas relacionadas ao estado da arte atual, propõe-se o *framework* denominado de SmartLVEnergy, do inglês *Smart Low-Voltage Energy*. A proposta deste *framework* consiste na otimização dos sistemas de energia de baixa tensão com protocolos e interfaces adaptáveis, viabilizando o gerenciamento avançado de energia em infraestruturas legadas. Isto é promovido através da integração de plataformas de *retrofit* baseadas em elementos sensores e atuadores, comunicando-se através de protocolos de comunicação compatíveis com a infraestrutura existe ou mais viável ao cenário existente.

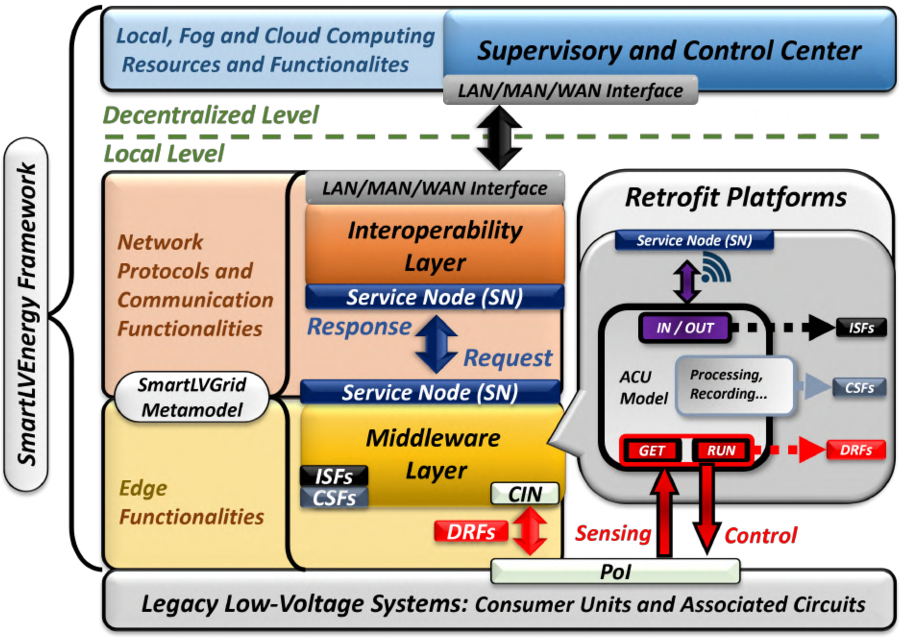
O desenvolvimento e implantação das plataformas de *retrofit* segue as premissas da modelagem dos ACUs, descrita no metamodelo SmartLVGrid, e, portanto, atuam com *middlewares* realizando a interface entre as entidades legadas e as plataformas digitais de supervisão e controle. Desse modo, as plataformas de *retrofit* podem incorporar e implementar as chamadas DRFs, ISFs e CSFs, primitivas operacionais do *SmartLVGrid*.

Na prática, o SmartLVEnergy implementa as definições e protocolos do metamodelo SmartLVGrid para a concepção de estratégias sistemáticas de soluções IoT e AIoT no contexto energético. Enquanto o metamodelo define padrões e diretrizes essenciais para a integração, expansão e interoperabilidade das tecnologias empregadas, o SmartLVEnergy organiza e padroniza a implementação de soluções digitais, garantindo adaptabilidade e escalabilidade para diversos cenários e necessidades energéticas. Dessa forma, o SmartLVEnergy se caracteriza como um *framework*, por oferecer uma estrutura robusta e flexível que orienta e facilita o desenvolvimento e a integração de recursos eficientes para a gestão energética.

No entanto, com a proposta de expansão da aplicabilidade do referido metamodelo, as CSFs, que gerenciam recursos computacionais como armazenamento e processamento de informações, também incorporam capacidades de processamento de borda, como modelos preditivos baseados em aprendizado de máquina. Este aspecto, não delineado no metamodelo original, define as funcionalidades de processamento ou preditivas podem ser integradas por meio das plataformas de *retrofit*. Dessa forma, parte do processamento realizado em um servidor local, na nuvem ou na névoa, pode ser executado na borda, mostrando o potencial deste *framework* para distribuição e descentralização dos recursos computacionais existentes para gerenciamento energético dos sistemas legados, não apenas na rede de distribuição de baixa tensão, mas nos setores prediais, residenciais e industriais, transcendendo o escopo do SmartLVGrid.

O *framework* SmartLVEnergy destaca-se por sua capacidade de garantir a compatibilidade e o máximo aproveitamento da rede e das instalações elétricas, enquanto aproveita o potencial da computação em Nuvem, Névoa e Borda, incluindo aplicações TinyML para gerenciamento de energia. O SmartLVEnergy, portanto, marca um avanço significativo, preenchendo a lacuna entre o monitoramento, controle em tempo real e análises preditivas de ponta, baseadas em soluções práticas e sustentáveis voltadas ao gerenciamento de energia de sistemas legados de baixa tensão. Essa abordagem melhora a eficiência energética e alinha-se com os objetivos globais de sustentabilidade (Bibri *et al.*, 2024), avançando a literatura na transformação digital das práticas de gerenciamento de energia. A Figura 4 ilustra a pilha do SmartLVEnergy. Mais detalhes sobre seus componentes são discutidos nas subseções 2.5.1, 2.5.2 e 2.5.3.

Figura 4. A pilha de protocolos do SmartLVEnergy.[1] (©2024 IEEE)



Fonte: (Fernandes *et al.*, 2024).

[1] ©2024 IEEE. Reprinted, with permission, from R. Fernandes, C. Costa, R. Gomes and N. Vilaça, "SmartL-VEnergy: An AIoT Framework for Energy Management through Distributed Processing and Sensor-Actuator Integration in Legacy Low-Voltage Systems,"in *IEEE Sensors Journal*, in May, 2024.

2.5.1 Recursos e Funcionalidades Computacionais

O *framework* SmartLVEnergy emprega um conjunto integrado de funcionalidades e recursos de computacionais distribuídos e descentralizados para implementar e melhorar a eficiência operacional dos sistemas de supervisão e controle. Ao aproveitar a computação local, o *framework* garante resposta imediata e privacidade de dados para tarefas de análise e controle em tempo real, minimizando a latência e reduzindo a dependência de redes externas. A computação em névoa aprimora ainda mais essa capacidade, trazendo serviços de computação, armazenamento e rede mais próximos aos dispositivos finais, melhorando o gerenciamento de dados e a confiabilidade de aplicativos em sistemas distribuídos com latência reduzida. Enquanto isso, a computação em nuvem oferece armazenamento expansivo e poder de processamento, permitindo aos centros de supervisão e controle o compartilhamento, processamento e análise avançada de informações.

2.5.2 Protocolos de Rede e Funcionalidades de Comunicação

Este componente é dedicado aos protocolos que permitem a interoperabilidade entre as plataformas de *retrofit*. Esses protocolos facilitam o envio de solicitações e o recebimento de respostas dos centros de supervisão e controle. Juntamente com a estrutura e encapsulamento das mensagens transmitidas, os protocolos devem ser utilizados de acordo com os padrões de comunicação existentes ou adequados para maximizar o uso da infraestrutura de rede de comunicação pré-existente. Além disso, essa camada também habilita funcionalidades de aplicação, como atualizações de *firmware over-the-air* (OTA) para plataformas de *retrofit*.

2.5.3 Funcionalidades de Borda

Este componente delineia a capacidade de processamento e predição a ser implementada através de plataformas de *retrofit*. Isso inclui a integração de tarefas de processamento com dispositivos sensores e atuadores, e a execução ou treinamento de modelos de aprendizado de máquina em proximidade com a camada legada. Essa proximidade aprimora o processo de tomada de decisão, pois permite ação direta sem depender das infraestruturas de rede para retransmitir dados para o centro de controle e supervisão, que normalmente requer acesso à internet e processamento adicional de dados. Além de reduzir a latência, essa camada oferece recursos para implementar funcionalidades de AIoT na borda para facilitar a implantação de soluções de TinyML, avançando o gerenciamento inteligente de energia em instalações legadas.

3 ARTIGOS PUBLICADOS

3.1 CONTRIBUIÇÕES DOS ARTIGOS PARA O FRAMEWORK PROPOSTO

Para conceber e validar o *framework* SmartLVEnergy conforme a hipótese e os objetivos estabelecidos, as experimentações realizadas na pesquisa se concentraram em unidades consumidoras prediais e industriais brasileiras com características legadas, regidas pela ANEEL. Validadas por meio de três artigos científicos publicados, essas experimentações basearam-se em modelos sistemáticos que impulsionaram a concepção do *framework* proposto, para desenvolver e implantar *clusters* de monitoramento com sensores e recursos computacionais para visualização, análise e predição de dados de demanda de energia. Utilizando redes de dados e interfaces físicas e lógicas padronizadas, e compatíveis com as infraestruturas existentes, garantiu-se a interoperabilidade dos sistemas legados com soluções tecnologicamente emergentes e promoveu-se a gestão energética nessas instalações, conforme diretrizes da ANEEL, por meio de recursos computacionais alocados em borda, localmente e em nuvem.

O Artigo 01, denominado "*A Retrofit Strategy for Real-Time Monitoring of Building Electrical Circuits Based on the SmartLVGrid Metamodel*", descreve uma estratégia sistemática de *retrofit* para incorporar ferramentas de gestão energética em instalações prediais legadas, em conformidade com os padrões da ANEEL. O trabalho foca na capacidade do monitoramento em tempo real dos circuitos, a partir do *retrofit* de quadros de distribuição de energia elétrica. Os dispositivos responsáveis pelas interfaces físicas e lógicas para aquisição de dados da infraestrutura existente foram desenvolvidos com base na adaptação de primitivas operacionais inspiradas nas pilhas de protocolos do metamodelo SmartLVGrid, viabilizando a expansão da proposta para outros casos e sistemas na esfera da gestão energética. Esta iniciativa englobou o desenvolvimento de hardware, *firmware* e soluções de comunicação sem fio em barramento, bem como uma aplicação de *software* hospedada em nuvem, projetados para se ajustar e validar as premissas do modelo proposto. Por meio disso, realizou-se um estudo de caso para mitigação e redução da demanda energética da instalação, para reduzir ultrapassagens de demanda contratada junto a concessionária de energia da unidade consumidora em estudo. Resultados parciais deste trabalho também foram publicados no trabalho "*Uma estratégia de retrofit para detecção de ultrapassagens de demanda em sistemas prediais legados*", referenciado no Apêndice A.

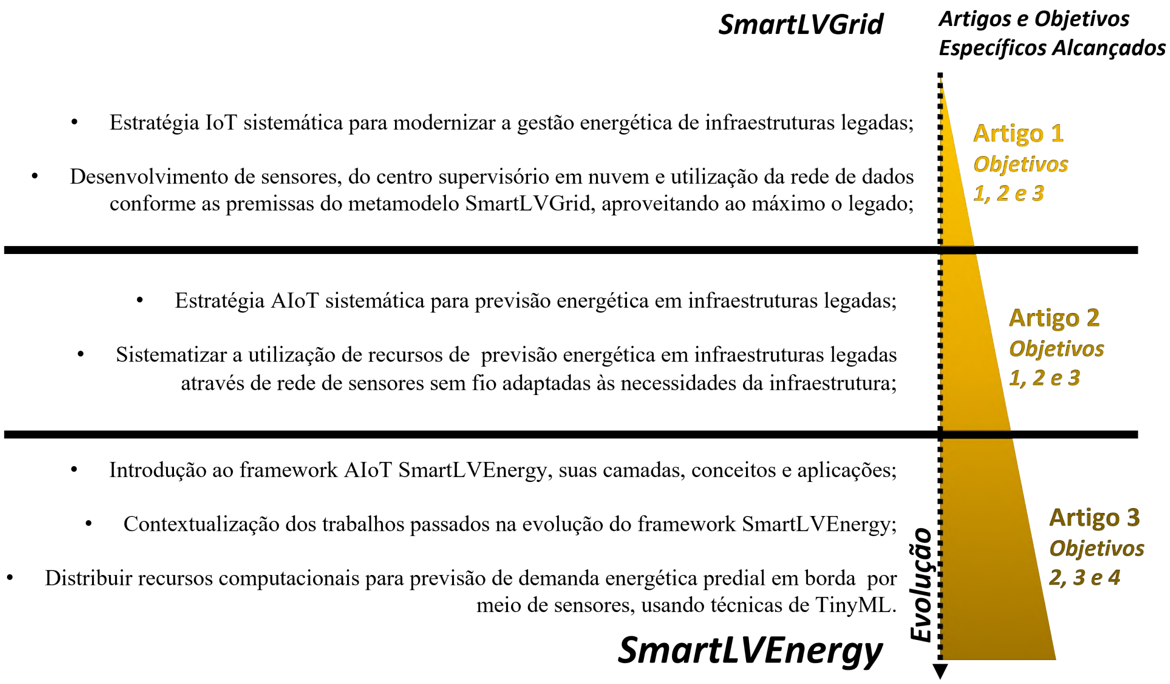
Em seguida, o Artigo 02, intitulado "*A Demand Forecasting Strategy Based on a Retrofit Architecture for Remote Monitoring of Legacy Building Circuits*", surge como uma continuação refinada do artigo anterior. O trabalho foca em uma estratégia AIoT sistemática, baseada em *retrofit* e também inspirada em adaptações no metamodelo SmartLVGrid, para monitoramento e predição das demandas de energia de uma instalação legada e dos circuitos que a compõem. Neste trabalho, houve um aprimoramento no hardware de monitoramento em relação ao Artigo

01, tornando-o mais robusto. A pesquisa foi realizada em uma instalação fabril pré-existente. Uma das contribuições deste trabalho foi a integração de uma rede sem fio *Peer-to-Peer* (P2P) adaptada para o monitoramento de circuitos em quadros legados de distribuição industrial. Alinhado às normativas da ANEEL, o trabalho apresenta uma ferramenta para previsões de demanda de curto prazo, para os próximos 15 minutos, para antever possíveis picos de demanda e evitar onerações adicionais com ultrapassagens de demanda contratada. Durante o estudo, foi possível avaliar modelos de previsão de séries temporais de demanda energética, desde a etapa de pré-processamento de dados até a otimização e análise de resultados. A metodologia utilizada na otimização dos modelos foi validada no trabalho *A Bayesian Optimization Approach of Ensemble and Decision Tree Learning Applied to Industrial Energy Consumption Prediction*, referenciado no Apêndice A. Também foi proposta uma alternativa para obter dados energéticos de unidades consumidoras legadas, abordando uma lacuna pouco explorada na literatura.

Apesar das contribuições substanciais dos Artigos 01 e 02 em preencher parte das lacunas identificadas no estado da arte, o metamodelo SmartLVGrid já estava sendo expandido e implementado além de sua concepção inicial, para aplicação e desenvolvimento de soluções específicas no domínio da gestão energética, convergindo as estratégias propostas para caracterização de um *framework*, segundo as definições de (Josey, 2016). Dessa forma, o Artigo 03, intitulado "*SmartLVEnergy: An AIoT Framework for Energy Management through Distributed Processing and Sensor-Actuator Integration in Legacy Low-Voltage Systems*", aborda as definições e conceitos deste *framework* e fundamenta as propostas dos trabalhos anteriores em um escopo ainda mais abrangente. O SmartLVEnergy não apenas incorporou as primitivas do metamodelo SmartLVGrid, mas também facilitou a implementação e aplicação dessas primitivas, contribuindo para a redução da dependência de infraestrutura centralizada, ao alocar recursos de computação distribuída para infraestruturas legadas, permitindo um gerenciamento de energia descentralizado com capacidades de previsão, sensoriamento, controle, armazenamento e processamento de dados. Este estudo introduziu inovações, como previsões de demanda de energia de curto prazo realizadas diretamente nos sensores, em conformidade com os padrões da ANEEL, permitindo o processamento distribuído de informações críticas em instalações existentes com sensores adaptados. Assim, o *framework* ofereceu uma via sistemática para o desenvolvimento de soluções TinyML aplicáveis a uma ampla gama de sistemas elétricos de baixa tensão em diversos ambientes de forma sustentável e econômica, preservando a infraestrutura existente e servindo como modelo para viabilizar a gestão sustentável de energia em diversos contextos.

A Figura 5 exibe as contribuições da pesquisa para alcançar os objetivos esperados, correlacionando-as com a evolução do *framework* SmartLVEnergy a partir de cada trabalho publicado que compõe esta tese.

Figura 5. Contribuições das publicações para evolução do SmartLVEnergy.



Fonte: Autoria Própria.

A partir da próxima seção deste capítulo, serão exibidas as publicações que compõem os resultados e experimentações desta tese para validação e concepção do *framework* SmartLVEnergy, bem como as perspectivas futuras da pesquisa conduzida em cada um dos trabalhos.

3.2 ARTIGO 01 - A RETROFIT STRATEGY FOR REAL-TIME MONITORING OF BUILDING ELECTRICAL CIRCUITS BASED ON THE SMARTLVGRID METAMODEL

3.2.1 Resumo

O paradigma da Internet das coisas (IoT) promove o surgimento de soluções para viabilizar estratégias de gerenciamento de energia. No entanto, essas soluções podem favorecer o descarte ou substituição de sistemas obsoletos, mas ainda necessários. Assim, uma proposta que preconize o retrofit de sistemas pré-existentes seria uma alternativa para implementar o monitoramento e gerenciamento de energia. Nesse sentido, este trabalho apresenta uma estratégia de monitoramento de parâmetros elétricos em tempo real por meio de soluções IoT, aplicações hospedadas em nuvem e retrofitting de sistemas elétricos prediais legados. Nesta implementação, adaptamos o metamodelo SmartLVGrid para sistematizar a inserção de recursos de monitoramento remoto em circuitos de baixa tensão. Para isso, desenvolvemos plataformas embarcadas para monitoramento dos circuitos de um quadro elétrico predial e uma aplicação para visualização e armazenamento de dados na nuvem. Com isso, foi realizado o monitoramento remoto da unidade consumidora em relação à demanda de energia, fator de potência e eventos de variações de parâmetros elétricos nos circuitos do quadro de distribuição legado. Também realizamos um estudo de caso com o sistema proposto, identificando eventos de ultrapassagem de demanda contratada na unidade consumidora, mitigando a contribuição individual dos circuitos da instalação neste processo. Portanto, nossa proposta apresenta uma alternativa para viabilizar a gestão energética e aproveitamento máximo dos recursos existentes.

3.2.2 Revista

- Energies - MDPI (ISSN: 1996-1073).
- Qualis A2 (2017-2020), JCR: 3.0, CiteScore: 6.2.
- Website: www.mdpi.com/journal/energies.
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3.2.3 Corpo Editorial

- Prof. Dr. Rongyue Zheng. Faculty of Civil and Environmental Engineering. Ningbo University, China.
- Dr. Li Huang. Faculty of Civil and Environmental Engineering. Ningbo University, China.

3.2.4 Publicação

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Article

A Retrofit Strategy for Real-Time Monitoring of Building Electrical Circuits Based on the SmartLVGrid Metamodel

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Abstract: The Internet of things (IoT) paradigm promotes the emergence of solutions to enable energy-management strategies. However, these solutions may favor the disposal or replacement of outdated but still necessary systems. Thus, a proposal that advocates the retrofit of pre-existing systems would be an alternative to implement energy monitoring. In this sense, this work presents a strategy for monitoring electrical parameters in real time by using IoT solutions, cloud-resident applications, and retrofitting of legacy building electrical systems. In this implementation, we adapted the SmartLVGrid metamodel to systematize the insertion of remote monitoring resources in low-voltage circuits. For this, we developed embedded platforms for monitoring the circuits of a building electrical panel and application for visualization and data storage in the cloud. With this, remote monitoring of the consumer unit was carried out in relation to energy demand, power factor, and events of variations of electrical parameters in the circuits of the legacy distribution board. We also carried out a case study with the proposed system, identifying events of excess demand in the consumer unit, mitigating the individual contribution of the installation circuits in this process. Therefore, our proposal presents an alternative to enable energy management and maximum use of existing resources.

Keywords: retrofit; SmartLVGrid; real-time systems; IoT; energy monitoring; energy efficiency

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1. Introduction

Society drives the development of new technologies for automation, processes, and systems in the most diverse sectors. Industries, cities, homes, and building installations are examples of environments with constant technological transformations. In this context, the digital paradigms of this millennium, such as Industry 4.0, Internet of things (IoT), smart grids, smart cities, and smart buildings, promote technological convergence processes by using digital integration solutions for monitoring and control of assets and inputs [1]. In addition, through digital paradigms it is possible to optimize the assets present in these environments, promoting flexibility, scalability, dynamism, and efficiency, in addition to other socioeconomic benefits [2].

The digital transition obtained from the implementation of these paradigms can occur abruptly or not [3]. The implementation time and the cost of digital solutions for this are preponderant factors, because short-term transformations may require larger investments. Usually, these types of solutions promote the disposal or replacement of resources that could still be useful or with acquisition costs not fully amortized [4]. In such cases, it is necessary to employ processes that steer the technological transition gradually through strategies based on leveraging legacy resources; otherwise, these processes would only be feasible for absolutely new solutions.

The electricity sector, indispensable for the realization of many social and economic practices, maintains much of its legacy structure from its conception [5]. This involves performing manual processes to carry out maintenance and management of the legacy electrical systems in operation [4]. Thus, specialized professionals are still needed in the field to perform these activities, which makes it difficult to record and access data in real time or which, occasionally, may lead to failures or field accidents. Thus, the implementation of digital paradigms provides the opportunity for the emergence of new techniques to automate electrical systems and enable energy management and efficiency. In this sense, IoT solutions can be employed in energy-efficiency strategies through the addition of real-time communication capabilities, distributed computing processing, and the control and sensing of objects through interconnection in data networks [6,7]. In smart grids and smart building models, in which the automation of electrical systems is widely applied, IoT solutions ensure safety, efficiency, and maximum system excellence in their operations [8–11]. However, despite the use of IoT in implementing new solutions for energy monitoring and control, there is a lack of strategies to integrate new solutions with legacy electrical systems.

The retrofit strategy, on the other hand, presents itself as a solution to this problem. Through retrofitting, it is possible to update and customize old or technologically outdated but still necessary systems, in order to preserve them and reduce costs in the addition of new functionalities in legacy systems [12]. In addition, this strategy enables a gradual rather than an abrupt technological transition in legacy electrical systems, making the maximum use of pre-existing resources. Still, in order for retrofit to be used systemically in the upgrade and integration of legacy electrical systems with IoT solutions, it is necessary to use a reference model based on architectural definitions endowed with standardized logic layers, protocols, and interaction interfaces applied to the specificities of this particular context. However, the literature presents few works that employ retrofit techniques from reference models to standardize their implementations, especially in the electrical sector.

At [5], the authors proposed a reference metamodel for smart grids, named SmartLV-Grid. It enables the transition from a legacy passive low-voltage power distribution plant to the smart grid paradigm by using the retrofit strategy in conjunction with systems engineering concepts. SmartLVGrid is composed of protocol stacks that enable the integration of legacy structures with compatible middleware (hardware and firmware). In addition, these protocols specify how to realize the logical link (interoperability) of the developed middlewares with a supervision and control center.

Interoperability, scalability, flexibility, and system efficiency are some of the essential aspects to make energy management in the electricity sector viable, developed, and mature [13]. However, the SmartLVGrid metamodel does not address methods or resources that advocate data analysis for real-time energy management, including virtualization and integration of legacy systems with IoT solutions and computational tools such as cloud computing, dashboards, and databases, for example. With data presented centrally in the cloud, it is possible to use virtual environments to manage energy consumption more effectively [14]. From this, we proposed a new method for managing low-voltage legacy circuits based on the adaptation of the SmartLVGrid metamodel and the use of the retrofit strategy. This way, we were able to make the most of pre-existing resources, in addition to providing technological means to analyze energy efficiency by monitoring electrical parameters with interactive dashboards in cloud software applications. In this context, no studies were found in the literature that carried out investigations or practical implementations of strategies, including a reference model and the use of retrofit, as the authors in [5] found, to perform energy management in the proposed way.

In this article, we present a strategy, which employs IoT solutions, retrofit of legacy electrical systems and cloud-resident applications, for real-time monitoring of legacy electrical parameters and energy management. As a proof of concept, the proposed strategy was used to insert energy-monitoring resources in building circuits of a low-voltage power distribution board. To implement remote monitoring, we developed embedded hardware platforms and, respectively, their firmware, in order to implement the middleware and interoperability layers of our adaptation of the SmartLVGrid metamodel, but adapted to meet the circuits of the switchboard in use. Throughout this article, the details of the software applications and platforms developed are described, at the physical and architectural levels, with the necessary information to make it possible to use the same methodology in the implementation of new solutions and guarantee the insertion of new functionalities, preserving as much as possible the legacy infrastructures. In this sense, we raise the following contributions related to this work.

(1) We introduce energy monitoring through the adaptation of the SmartLVGrid metamodel, use of IoT solutions, and the use of the retrofit strategy in a systemic way, enabling energy management and maximum preservation of legacy electric circuits.
(2) We develop hardware devices and their respective firmware, enabling the retrofit of the circuits of a distribution board, based on the premises of the reference model.
(3) We develop a software application for circuit virtualization, with dashboards, database and cloud computing resources, systematically integrated with the implementation of the metamodel adapted in this work.
(4) We present the resources for monitoring the electrical quantities of each legacy circuit of a low voltage building switchboard.

To present the proposal of this article, we divided the sections as follows. In Section 2, we present a survey of the state of the art related to the theme. In Section 3, we present a survey of the theoretical framework for the implementation of our proposal. Section 4 presents our model proposal, based on the retrofit of legacy low-voltage circuits of a power distribution board. In Section 5, we present the materials and methods used, making them compatible with the architecture exposed in the previous section. In Section 6, we present the results obtained. In Section 7, we present the conclusions, along with proposals for future work.

2. Related Work

2.1. Energy Monitoring Solutions in the Context of the IoT Paradigm

Energy monitoring improves efficiency and management in the electricity sector, enabling analysis of the grid's electrical parameters, the demand consumed and the power quality, and providing managers with resources (e.g., computational and data) for decision making. In this context, IoT solutions contribute to provide remote and real-time monitoring and control in the residential, building, industrial and metropolitan sectors, interconnecting devices to the energy system and integrating these devices with computing systems, including cloud solutions [15,16].

Real-time applications enable monitoring in deterministic time, without conflicts and in a prioritized manner so that all events and tasks are executed as expected. The relevant literature presents work with real-time IoT solutions to implement energy-monitoring systems. At [17], real-time energy monitoring was implemented via interconnected hardware devices in a narrowband IoT (NB-IoT)-based mobile network for smart grid applications. Similarly, the authors of [18,19] have developed hardware devices to make energy-consumption data available in real time to users over a wireless data network. The authors of [20] used the Raspberry Pi 3 platform as an interface between an energy meter and a graphic application for displaying data obtained in real time. At [21], the authors exposed a study evaluating the performance of different real-time IoT solutions. On the other hand, the authors of [22] presented a decentralized solution for real-time energy monitoring from mobile devices.

In addition to real-time communication and monitoring, IoT solutions use computing resources for data storage, processing, and visualization to analyze and expose parameters for decision-making. From these, it is possible to elaborate databases to analyze and expose the main parameters of value for decision making. In this sense, the literature presents works that use these resources in energy monitoring applications. In [23], the authors used structured query language (SQL) databases, along with the graphical interfaces of the developed application, to store and display the main electrical parameters and the consumed demand of a building circuit. The authors of [24] presented energy consumption and temperature measurements of a climate control system by using interactive dashboards. At [25], the authors discussed IoT solutions for energy monitoring, including cloud data storage and processing.

It is important to comment on the contributions of the literature in the IoT area for improving energy efficiency. In this area, proposals involve energy-demand management and power quality analysis of facilities. Energy-demand management uses monitored data to develop strategies and make decisions for reducing energy consumption. The authors of [26] presented a survey of the energy demand consumed by the School of Telecommunication Engineering of the Polytechnic University of Madrid over the course of one year. From the obtained data, the authors used a wireless network that employed market devices to control the energy demand in the school. On the other hand, the authors of [27] managed the energy demand of residences in a Simulink software model, considering the insertion of renewable sources and networked devices. In addition, the work [28] described an energy-management system that uses real-time IoT platforms in order to improve energy efficiency.

Proposals in the literature that use IoT for facility power quality analysis seek to improve power quality in metropolitan, industrial, building, or residential settings. In the works [29–32], for example, the authors have developed hardware devices to remotely monitor voltage sags, swells, and the electrical parameters of the circuits used. In [33], the authors proposed an algorithm for disturbance and event analysis in the context of power quality. For this, they employed real-time IoT devices in monitoring the parameters and stored the obtained data in the cloud for further use of the algorithm. In [34], the authors motivated the need to monitor electrical parameters to improve power supply reliability and power quality. In this same work, the authors also presented the development of a device capable of remotely monitoring the number and duration of power interruptions and voltage variations on both sides of circuit switching devices, with the possibility of local storage in case of failures of communication.

Tables 1–4 summarize the works associated with the context of this article and cited in the subsection. However, in our literature search, we did not find works that use retrofit strategies to take advantage of legacy systems based on IoT solutions and computational resources in order to offer resources to improve energy efficiency and power quality. Thus, the solutions exposed are focused on the particular context of their applications, which may make it infeasible to implement the proposed strategies in other cases. In addition, we did not find studies that propose metamodels capable of providing the insertion of automation, electronic control, distributed processing and communication resources in electrical systems from retrofit techniques for the same purpose of energy management.

Table 1. Works with emphasis on energy efficiency.

Work	Year	Application
[26]	2021	Demand control from WSN
[27]	2018	Demand Management with Renewable Sources
[28]	2019	Demand Management with IoT Solutions

Table 2. Works with emphasis on computational resources for energy management.

Work	Year	Application
[23]	2019	Use of databases and interfaces to display electrical parameters and the demand of a circuit
[24]	2018	Interactive dashboards for consumption display energetic
[25]	2021	Methods of viewing, storing and cloud energy data processing

Table 3. Work on real-time systems for energy monitoring.

Work	Year	Application
[17]	2020	Energy demand monitoring in a real-time NB-IoT network
[18–20]	2018, 2020 2020	Development of devices for real-time consumption monitoring
[21]	2020	Evaluation of real-time solutions for energy monitoring
[22]	2020	Decentralized monitoring solution energy in mobile devices

Table 4. Work with emphasis on power quality analysis.

Work	Year	Application
[29–32]	2019, 2018 2019, 2021	Devices for monitoring sags, swells and electrical parameters
[33]	2020	Algorithm for disturbance and event analysis of power quality with IoT devices
[34]	2020	Development of a device and an algorithm applied to the remote monitoring of power interruptionsand voltage variations in switching circuits

2.2. Retrofit

The retrofit strategy uses techniques to take advantage of old but still necessary systems, through the inclusion of new features [12]. However, the use of this strategy requires prior and specific knowledge of the pre-existing elements and infrastructures, in order to perform the proper interfaces for implementation of the desired functionalities without causing damage or accidents.

The integration of legacy systems with digital ecosystems by using retrofit and IoT techniques is a well-cited topic in the literature. In [35], the authors propose strategies for using retrofit to reduce energy consumption and improve the comfort of legacy building facilities. The authors of [36] implemented a wireless sensors network (WSN) for controlling and monitoring legacy air conditioners from retrofit devices. In [37], the author presented solutions for automation of legacy infrastructure using retrofit strategies. Also, the authors of [38] proposed a model based on the building energy management system (BEMS) method and the worldwide web consortium (W3C) specifications for monitoring and controlling energy consumption from a WSN, in the context of smart buildings, from a retrofit strategy.

Table 5 shows the retrofit works discussed above. These works presented satisfactory results regarding the technological upgrade of pre-existing systems using retrofit strategies. However, the proposed methods serve a pre-established number of cases and systems, making scalability, distributed processing, or even interoperability with other applications difficult. Furthermore, the authors did not employ generic architectural models to standardize the presented strategies in the use of larger numbers of devices, of the same nature or not. In contrast to the aforementioned works, the present work distinguishes itself by presenting retrofit techniques performed in a systemic way from a strategy and an architecture developed to promote energy management in legacy building circuits.

Table 5. Works with contributions from retrofit techniques.

Work	Year	Application
[35]	2015	Using retrofit to reduce energy consumption and improving the comfort of old buildings
[36]	2017	Using retrofit to enable control and air conditioner monitoring
[37]	2018	Retrofit Strategies for Automation legacy infrastructure
[38]	2021	Retrofit strategy for monitoring and control of energy consumption from a model based on the BEMS method and the W3C specifications

2.3. Middleware and Interoperability

Middlewares provide physical or logical interfaces between heterogeneous systems, and are challenges in terms of hardware and software development for IoT [39,40]. On the other hand, there are situations in which it is necessary to provide, in addition to physical or logical interfaces, interaction between different systems. In these cases, it is necessary to use methods that enable interoperability, especially in IoT applications that need to interact regardless of the communication protocol used [41,42]. Therefore, middleware and interoperability solutions are important allies in the integration of IoT solutions with legacy systems, reducing the complexity of integrating new technologies with existing resources and helping in the scalability of IoT applications.

The literature also presents work that enables technology convergence processes through interoperability middleware solutions. The authors of [43] proposed a method by which to realize interoperability of legacy industrial systems in the context of Industry 4.0 by employing minor changes to existing communication media. In [44], the authors proposed an architecture model to enable the interoperability and interconnection of devices located on the Malaga University campus, as a proof of concept for future applications of the model in smart city deployments. The work [45] presents a middleware solution that enables the interfacing of devices located in intelligent office environments. In [46], the authors deployed a smart grid model from a middleware architecture based on retrofitting legacy meters for monitoring electrical parameters in WSNs. The same authors, in [47], contributed a methodology to enable interoperability of legacy meters in smart grids from WSNs.

Table 6 presents the main characteristics of the above-mentioned works. These works contribute with solutions for standardization of technological convergence processes. However, they do not propose middleware solutions for energy management that make available physical and logical interfaces with legacy systems. Still, in the context of energy efficiency, the works do not present resources, which enables the communication interoperability of the proposed systems. Furthermore, the works in the literature did not conceive generic methodologies that could be applied to new systems and scenarios, beyond those exposed in the respective works. In this work, we proposed a generic architecture for retrofitting legacy building circuits, based on middleware and interoperability resources, which allows virtualization, communication and the insertion of IoT devices, enabling energy management from the monitoring of electrical parameters in real time.

Table 6. Work with emphasis on middleware and interoperability solutions.

Work	Year	Application
[43]	2017	Method for system interoperability legacy industrialists in the context of Industry 4.0
[44]	2019	Model for device interoperability in a university campus
[45]	2010	Middleware for device interface located intelligent office environments
[46]	2018	Model based on a middleware architecture for retrofitting legacy meters to WSNs
[47]	2018	Methodology for Enabling Interoperability of legacy meters from WSNs

2.4. Metamodels

Just as models are abstractions of some reality, metamodels are abstractions of models to design new modeling languages or extend existing modeling languages [48]. They are employed in the analysis, design, development, and integration of models for any system. This includes the integration of legacy systems with middleware and interoperability interfaces [1,49]. Therefore, metamodels enable the technological transition of pre-existing systems.

In this context, the literature exposes successful cases using the metamodel approach. In [50], the authors proposed an IoT metamodel to connect heterogeneous objects by using the premise of interoperability. The authors of [51] also implemented an IoT metamodel capable of transforming a software solution written in a specific modeling language for a Java application in order to standardize the development in a guided way. In [52], a metamodel was proposed for device interaction in intelligent environments from a modeling of relationships and attributes. In [4], the authors introduced a metasystem to enable the transition of legacy electric power distribution systems to the smart grids paradigm through the retrofit strategy. Table 7 presents the main characteristics of the aforementioned works.

Table 7. Papers with contributions based on metamodels.

Work	Year	Application
[50]	2018	Metamodel for device interoperability heterogeneous
[51]	2017	Metamodel for transforming solutions from software in a targeted manner
[52]	2016	Metamodel for device interaction in intelligent environments
[4]	2017	Retrofit-based meta-system for transition from legacy power distribution systems to the Smart Grid paradigm

Further on, the [4] metasystem evolved into the SmartLVGrid metamodel, which presents itself with primitives and protocols for using middleware solutions and interoperability resources through the retrofit of legacy low-voltage electrical systems [5]. Because this metamodel describes generic interfaces to be used for upgrading pre-existing systems, it is possible to extend the applications and resources made available by it to any technological niche, including in the electric sector itself. We found no other similar approaches in the literature to enable energy management in building environments from the individual monitoring of each circuit in the installation. Therefore, the SmartLVGrid metamodel is used as a basis to perform retrofits of electrical circuits enabling the remote monitoring of electrical parameters.

3. SmartLVGrid

Smart low-voltage grids (SmartLVGrid) is a metamodel for modeling legacy low-voltage circuits in power distribution systems based on the smart grid paradigm. It consists of a protocol stack and uses a retrofit strategy to add control, monitoring, and communication capabilities to pre-existing systems. This model is structured both at the local level, close to the final consumer, and at the central level, in the supervisory centers of the energy utilities. The geographical separation of these levels requires the use of local area network interfaces (LANs) or metropolitan area network interfaces (MANs) to establish logical links between the legacy systems and the operation and command centers. Figure 1 illustrates the protocol stack established in the SmartLVGrid model.

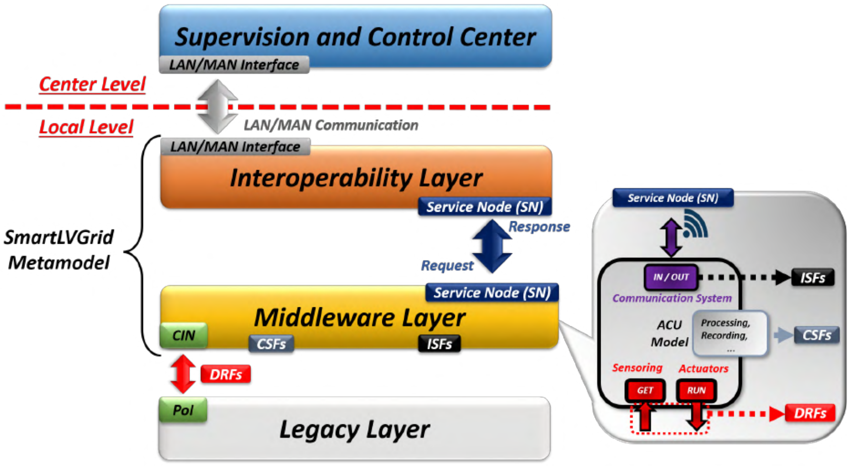


Figure 1. The protocol stack of the SmartLVGrid metamodel. The protocol stack of the SmartLVGrid metamodel [1].

As per Figure 1, the SmartLVGrid metamodel is composed of the interoperability and middleware layers. According to the metamodel, the retrofit is performed under the legacy structure at interface points called points of interface (PoI). The middleware layer interfaces with the legacy layer through the coupling and interaction node (CIN), allowing the execution of microprocesses called domain retrofitting functions (DRFs), one of the classes of operational primitives (OPs) of the metamodel.

The OPs are processes previously performed by field operators in the legacy electrical system that are now executed through service nodes (SNs) and CIN nodes, logical units responsible for the interfaces between the interoperability/middleware and middleware/legacy layers, respectively. The computational support functions (CSFs) implement processing and storage services in the middleware layer, and the interdomain support functions (ISFs) perform the communication processes in the same layer.

3.1. A Middleware Layer

The middleware layer is at the lowest level of the stack of the metamodel. Physically, this layer is implemented by means of retrofit devices, composed of embedded hardware, sensors, and actuators compatible with the DRFs to be executed. This layer is also called automation and communication unit (ACU), and its representation is illustrated in Figure 1. The representative model of the ACU consists of three ports: In/Out, Get, and Run. The communication processes and services of the ISFs are executed through the In/Out port. The Get port implements data collection by means of measurement and sensing DRFs. Finally, the Run port acts with control DRFs over the legacy layer. It should be noted that the ACU's processing and data storage routines are implemented through CSFs, as well as other computational support functions.

3.2. The Interoperability Layer

The interoperability layer is responsible for guaranteeing a set of rules and hierarchies and represents the infrastructure to implement network communication with the ACUs, aiming to interact remotely with these devices and use their functionalities. This layer classifies each ACU according to its position in the SmartLVGrid metamodel hierarchy. ACUs that supervise and monitor other ACUs and optionally run DRFs are called coordinators. ACUs that run DRFs on top of the legacy layer and are supervised by coordinators are called operators. In cases of expansion of the operating power system, which implies more computational capacity for the coordinator ACU, the metamodel provides subcoordinators for each cluster of operator ACUs. In this way, the subcoordinators will be associated with a single ACU coordinator that will communicate with the supervision and control center to pass on information about the system. It is important to note that each ACU has its own processing unit, enabling the distributed processing of the system from the retrofit of each legacy asset.

The supervision and control center retains all control and monitoring of the system from the communication with all coordinators present in the power grid. Other functions are the administration of the consumer units, distribution busbars and transformer stations. It is up to the technical–administrative staff of the supervision center to delimit the DRFs and autonomous decision-making to be performed by the retrofit devices.

4. Methodology for Implementing the Proposed System

SmartLVGrid was initially designed to be used in conjunction with low-voltage consumer units and their interfaces with the legacy electrical system [5]. However, in [1], the authors presented a model based on the retrofit of a legacy building lighting circuit, showing the feasibility of adapting SmartLVGrid for smart buildings. In this sense, the present work contributes by extending the SmartLVGrid model and using the retrofit method for a new load profile: the legacy electrical circuits of a power distribution board. The term legacy, in this case, refers to the fact that, previously, the circuits did not have any element that provided the execution of interoperability, control, or remote monitoring functionalities. Figure 2 illustrates the retrofit strategy developed.

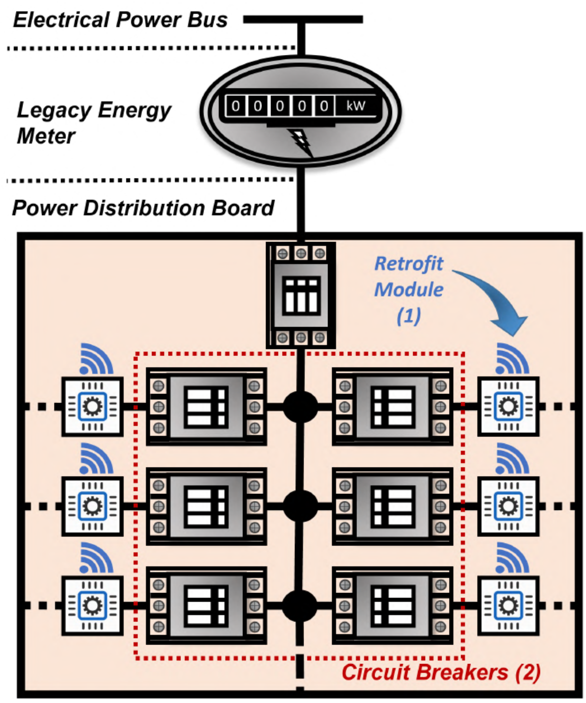


Figure 2. Proposed retrofit strategy for energy monitoring.

As illustrated, the strategy proposed in this work promotes the insertion of retrofit modules (1) consisting of specific hardware and firmware for network communication, processing, data storage, and for the acquisition of the electrical parameters of each circuit of the switchboard. It should be noted that the retrofit modules (1) are calibrated with a precision current and voltage source before being installed in the circuits. These modules (1) have been inserted next to the circuit breakers (2) of the power distribution board in order to

- standardize the development and installation of retrofit modules;
- reduce visual impacts by confining the solution within the switch cabinet;
- standardize the development and installation of retrofit modules; and
- preserve as much as possible the existing electrical installation

In this way, the disposal or removal of any element present in the circuit (cables, walls, socket points, circuit breakers, among others) was avoided. After retrofitting the circuits of the switchboard, it was possible to supervise them from a supervision and control center. In this work, the supervisory center is located in a cloud for accessing the monitored parameters from anywhere. In addition, the supervisory center was designed to provide energy management resources in real time, enabling the analysis of active demand consumed and other electrical quantities, such as voltages, currents, and power factor. It is noteworthy that the literature has not presented works with this approach, involving the extension and use of metamodels and retrofit techniques for this purpose. The tests of the proposal and the validation of the results were obtained from the integration of the retrofit modules with the supervisory center, through which it was possible to monitor, individually, each circuit and its respective electrical parameters and events.

The following section presents the modeling performed to extend the SmartLVGrid model and the conception of our proposal. Based on this modeling, it is possible to understand in more detail the hardware and software elements conceived for the development of our proposal and the adaptations made to the SmartLVGrid metamodel for the insertion of monitoring resources in the legacy building circuits of a distribution board.

4.1. SmartLVGrid Metamodel Adapted to the Proposed System

To insert a new load profile into the context of the SmartLVGrid metamodel, we extended the middleware and interoperability layers of this metamodel, creating the necessary interfaces to the switchboard circuits. These adaptations were made starting with the specifications of the operational primitives and the composition of the ACUs to be used. This also involves the methods for integrating the physical interfaces of the ACUs with the legacy switchboard circuits, detailed in the next section. In addition, the supervisory and control center was implemented by using cloud services with dashboards and databases, premises not explored by the original metamodel. Figure 3 illustrates the interfaces adapted from the SmartLVGrid metamodel for the proposal of this paper, along with the integration with the supervision and control center (SCC).

In this paper, retrofit modules for measuring electrical parameters act as ACU operators in the system. They were called ACU-BREAKERs, because they are located next to the circuit breakers of the legacy circuits. In addition, the proposed implementation relies on a router to communicate and interface with the cloud services responsible for housing the dashboard and database. Therefore, in the proposed architecture, this device has been classified as an ACU coordinator, and is referred to as ACU-ROUTER.

Figure 3 illustrates the interoperability between the ACUs over the local area network (LAN) interface. The ACU-ROUTER, in the role of coordinator, communicates with the supervisory and control center (SCC), which, in this paper, is located in the cloud next to the other computational services for visualizations and data processing in the context of energy efficiency and power quality. With the ACUs interconnected, each circuit can be virtualized by the SCC in order to individually organize the parameters obtained by each circuit. It should be noted that the interface point is located between the circuit breaker and the electrical circuit, from where the Get port extracts the measurement data up to the CIN. In this case, the service nodes act as the interface of the available communication media with the LAN network, providing the data and access paths for this (TCP ports, IP addresses, SSID, among others). The following subsection presents a brief description of the architecture of each ACU developed in our proposal.

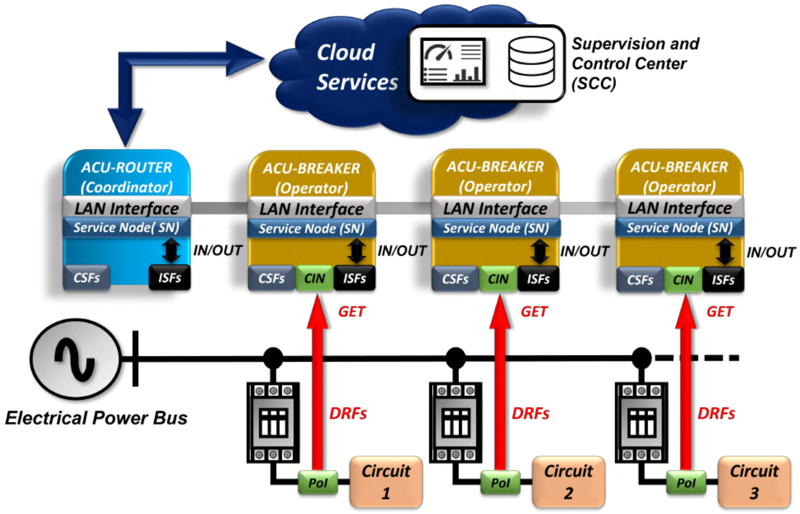


Figure 3. SmartLVGrid architecture adapted to the proposed model.

4.1.1. ACU-BREAKER Modeling

Figure 4 exposes the architecture diagram of the ACU-BREAKER and its interfaces. As mentioned, this ACU is responsible for collecting the electrical parameters of the legacy circuit associated with its respective breaker. The measurement of the electrical parameters, according to the SmartLVGrid metamodel, is characterized as a DRF executed by the Get port of this ACU. Similarly, the communication of this ACU is done through the In/Out port, responsible for executing the ISFs of requests and responses to the ACU coordinator (ACU-ROUTER). Moreover, the ACU-BREAKER has CSFs associated with data storage, device configuration, and network connection management. To perform the abovementioned operational primitives, it should be noted that this ACU has digital processing resources for acquisition and adjustments of the measured electrical parameters, communication, transduction, and conditioning of electrical signals, and also protection against possible overcurrent and overvoltage surges.

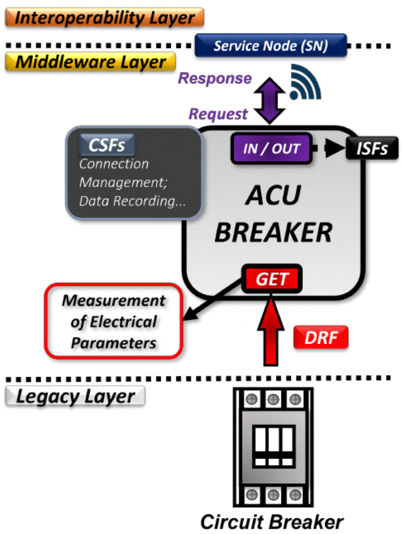


Figure 4. ACU-BREAKER architecture diagram.

4.1.2. ACU-ROUTER Modeling

Similarly, Figure 5 illustrates the ACU-ROUTER architecture diagram and its respective interfaces. Although this ACU does not have interfaces with the legacy layer and does not have Get and Run ports for DRF execution, it plays an important role in the proposed system. Through it, it is possible to interface the ACU operators, responsible for measuring the electrical parameters, with the supervisory control center (SCC), which is located in the cloud. The ACU-ROUTER/SCC interface is also performed through In/Out ports, by means of ISFs associated with request and response messages. Regarding CSF, the ACU-ROUTER performs the connection management of the ACU operators on the data network used.

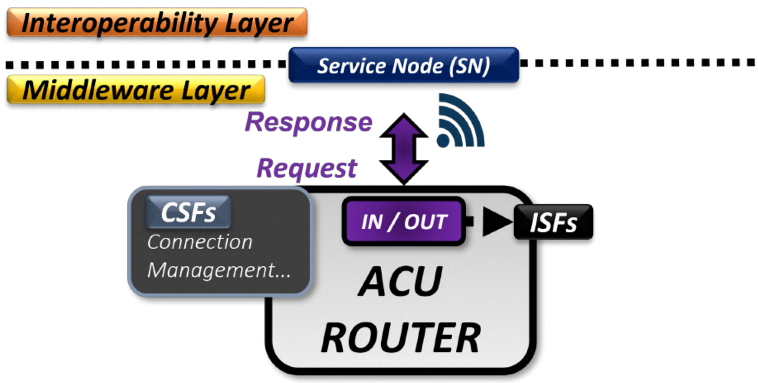


Figure 5. ACU-ROUTER architecture diagram.

5. Materials and Specifications for System Implementation

This section presents the strategies used to develop the middleware and interoperability layers and the supervision and control center (SCC) of the monitoring system in this paper. To this end, the software features, message exchange patterns, and hardware and firmware specifications of the retrofit modules will be defined, according to the specifications of our proposal.

5.1. Definition of the System Interoperability Layer

Because our proposal is based on retrofit, we reused existing network and infrastructure resources in the scenario used for the case study. In this sense, to provide network interconnection for the ACUs, we reused the wi-fi network infrastructure available in the vicinity of the power distribution board and jointly employed the MQTT communication protocol. From this, we established the premises to enable interoperability with the ACU devices in our proposal.

We used the Mosquitto MQTT broker running on a cloud-resident virtual machine (DigitalOcean Droplet), along with the applications and software services of the SCC. The packets were transmitted in the system with QoS 0, to reduce the latency of the data exchange between the ACUs and the broker [53,54]. The virtual machine's IP address and TCP port 1883 were used to provide access to the MQTT broker. This address and port was passed to the firmware for networking the ACUs via messages presented later in the paper. Thus, the service nodes (SNs) recommended in the metamodel were implemented with the establishment of the network connection of the ACUs to the MQTT broker. It is important to mention that in order to have interoperability between the ACU-ROUTER and ACU-BREAKER middleware, the In/Out ports and the SNs must use the same standard and communication network.

To enable interoperability between ACUs via Wi-Fi LAN and the MQTT protocol, we used request and response messages in JSON format, implemented via the cJSON library [55]. Because the SCC is hosted in the cloud, its connection to the ACU-ROUTER takes place via the Internet. The MQTT messages were transmitted in the SCC/ACUs direction and the responses transmitted in the opposite direction. In this context, messages were used for electrical parameter requests, updating device network registration, and updating device calibration parameters. Figure 6 illustrates the process adopted to enable the communication of the ACUs with the cloud-hosted SCC, according to the proposed architecture, for a request to send electrical parameters as follows:

- The SCC, via the Internet, establishes communication with the Wi-Fi LAN interface of the ACU-ROUTER and ACU-BREAKER (1);
- The configuration of the service nodes (SNs) of the ACU-ROUTER and ACU-BREAKER is performed (2);
- The request message (3) is transmitted;
- By means of MQTT messages, the ISFs for synchronizing communication and sending data from the ACUs (4) are executed.

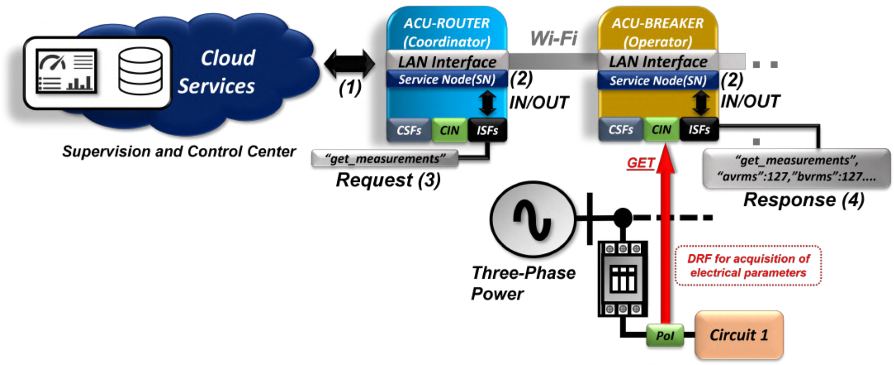


Figure 6. Communication process of the proposed system.

5.2. *Implementation of ACU-BREAKER Middleware*

The conception of the ACU-BREAKER was based on the development of a hardware device, and respective firmware, to monitor the electrical parameters in real time of a three-phase circuit located in a power distribution board, being possible to use it to monitor two-phase or single-phase circuits. To monitor the switchboard circuits through the retrofit strategy recommended in the proposed system architecture, we designed a panel containing six ACUs-BREAKER, power supplies, and battery backup for continuous operation in cases of power interruption. In this way, it is possible to detect power interruption or voltage and current variation events in cases of re-energization of the monitored circuits.

Each ACU panel was installed next to six circuit breakers in the switchboard. Thus, for 48 circuits present in the electrical panel, eight panels containing six ACUs each were developed. The ACU-BREAKER was designed with reduced dimensions in order to facilitate its installation. Figure 7 illustrates the strategy described above for installing the ACU-BREAKER and the hardware features present in its design. On the other hand, the main hardware components of the ACU-BREAKER are detailed in Figure 8, including the connections to the support board that distributes the power supplies and battery backup to each ACU.

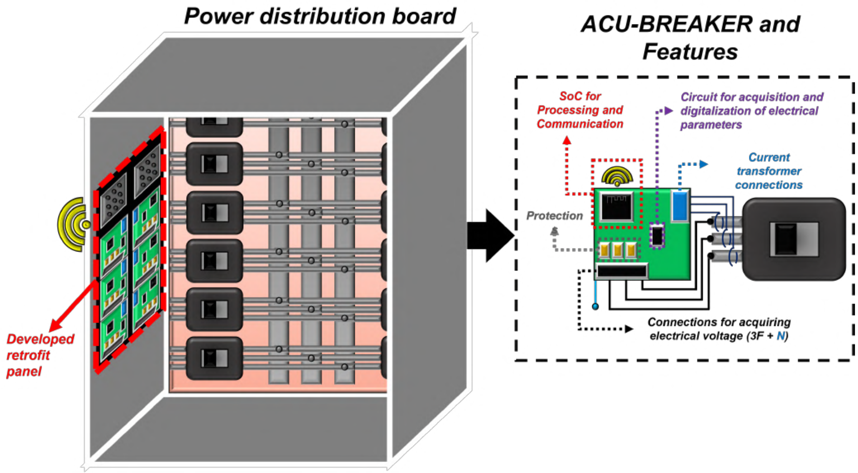


Figure 7. Strategy for using ACU-BREAKER.

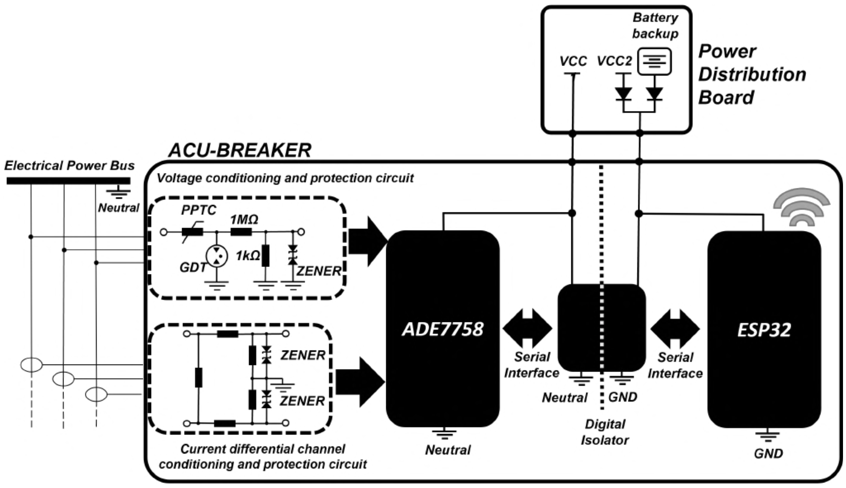


Figure 8. Main hardware components of the ACU-BREAKER.

5.2.1. SoC for Processing and Communication

As mentioned, the ACU-BREAKER has a system-on-a-chip (SoC), with processing and communication capabilities, through which we develop the DRFs, CSFs, and ISFs of the ACU. To do this, we used the ESP32-D0WD-V3 SoC present in the ESP32-WROOM-32E module from the manufacturer Espressif [56,57]. Through the ESP32 module, it was possible to take advantage of wi-fi communication resources and the MQTT protocol to implement the ISFs through request and response messages, and network connection management (one of the CSFs). In addition, the ESP32 module has serial communication peripherals used to debug the developed firmware and to communicate with the electrical signal acquisition circuitry. The ESP32-WROOM-32E module has a 4 MB flash memory, which was used to implement the CSF for storing the calibration settings parameters and for storing the communication network configuration parameters.

5.2.2. Circuit for Acquisition and Digitalization of Electrical Parameters

To ensure the reliability of the obtained electrical parameters, even in nonsinusoidal conditions, we chose to use an integrated circuit dedicated to the acquisition and digitization of the electrical parameters by means of the mean value technique. To do this, we employed the ADE7758 integrated circuit and the discrete components associated with it. This integrated circuit communicates with the processing unit by means of a serial interface and its function is to receive the electrical parameters of voltage and current previously conditioned, and then to digitize and process these parameters. The use of this integrated circuit in the ACU-BREAKER is detailed in Figure 8. Through this process, we obtained the parameters of effective voltage and current, network frequency and active, reactive and apparent power. The active, reactive and apparent power and power factor parameters were computed by the ESP32 module by using the active, reactive, and apparent power parameters obtained. All the technical aspects, equations, and diagrams used to support the use of the ADE7758 as commented above are detailed in its datasheet [58].

Through the integrated circuit ADE7758, we performed a procedure for calibration of the parameters obtained through gain and offset adjustments as described in its datasheet, ensuring the accuracy of the acquired values. To perform the calibration, we used a precision source, PPS400.3 from the manufacturer MTE [59], to provide known parameters of voltage and current. In this way, it was possible to adjust the gain and offset parameters based on the values provided by the precision source and the measurement performed by the ADE7758. We developed a routine in the firmware of the ACU-BREAKER to receive, adjust, and update the parameters in the internal registers of the ADE7758, as specified in its datasheet. It is important to note that each ACU-BREAKER was calibrated individually, as each was affected differently by the tolerance or precision of the components used for signal conditioning or transduction. In the tests performed, it was possible to obtain a measurement with about 1% error through the calibration adjustments. Figure 9 illustrates the ACU-BREAKER on a bench to be calibrated by using the precision source used.

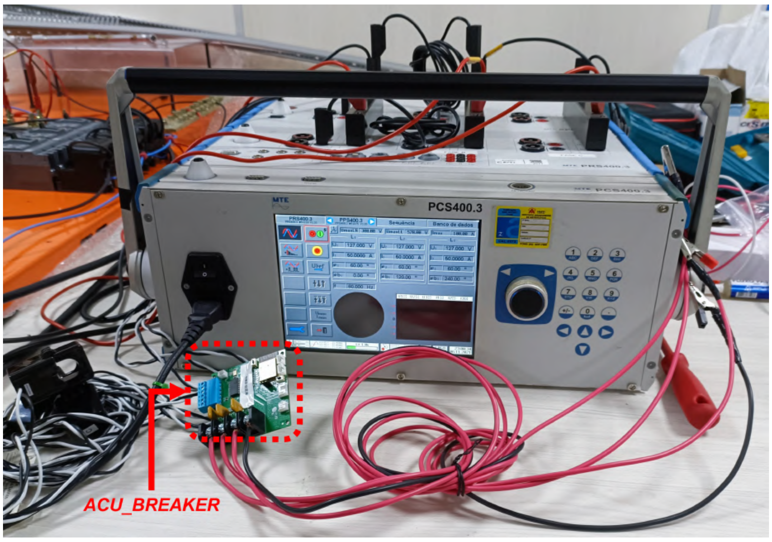


Figure 9. Benchtop ACU-BREAKER for calibration with precision source.

5.2.3. Protections and Connections for Measuring Voltage and Current

As illustrated in Figures 7 and 8, the ACU-BREAKER has discrete components responsible for the protection and conditioning of the electrical signals to be introduced in the integrated circuit ADE7758 and, which were previously obtained through the connections of acquisition of the electrical voltages and the connections with the current transformers with the differential channels of the mentioned circuit. It is important to note that these connections physically implement the Get port of this ACU.

The internal ADCs of the ADE7758 rely on pre-conditioned voltage and current signals with low values, being 500 mV the maximum peak value of the signals inserted into the three voltage and current channels [58]. Consequently, in order to be able to perform maximum 500 V peak readings from the mains, we set up the voltage transduction circuit by using a resistive divider to create the 500 mV/500 V ratio on the voltage channels. Considering the neutral as the reference, we use a resistive divider of 1 (MΩ) and 1 (kΩ) after the voltage connector. In this way we establish the conditioning of the voltage channels. It is important to note that the resistors used are accurate to 1%, to maximize the effectiveness of the system, and operate with powers of up to 250 mW, avoiding overheating due to the high electrical potentials to which they can be subjected.

The current transformers were sized to meet the circuit breaker currents. To meet this demand, we chose to use the noninvasive current transformers of the AcuCT mV series, produced by the manufacturer Accuenergy [60]. Regardless of the nominal current of these transformers, their full-scale outputs are 333 mV. However, to use them with the differential current channels of the ADE7758, it was necessary to make adjustments to the signals obtained from these transducers. The maximum full scale of the current channels is 500 mV peak, but it can be adjusted to 250 mV or 125 mV peak. In this sense, we used a resistive divider to adjust the current transformer output to 250 mV peak in each circuit and set the current channel full scale to the same value, changing the internal gain registers of the ADE7758.

Because the electrical voltage transduction is performed in a non-isolated manner, to ensure protection against surges, overcurrents and overvoltages, the input protections of the ACU-BREAKER voltage channels are composed of gas discharge tubes (GDTs), polymeric positive temperature coefficient (PPTC) resettable fuses and Zener-type diodes. To ensure the protection of the ESP-WROOM-32E module in serial communication with the ADE7758, we used a digital isolator to separate the main's neutral from the module's digital reference. Thus, it was necessary to use two power supplies in the panel of the designed ACUs, one for power supply to the ADE7758 and one for power supply to the ESP-WROOM-32E and its peripherals. On the other hand, the current channels rely on galvanic isolation and the noninvasive measurement of current transformers. Therefore, only Zener-type diodes have been used to prevent overdrafts from damaging the ACU-BREAKER current channels.

5.2.4. Electrical Schematic and Layout

The electrical schematic and layout of the ACU-BREAKER were developed in Altium 21 software. Figure 10 illustrates a three-dimensional (3D) perspective of the layout designed for the ACU-BREAKER.

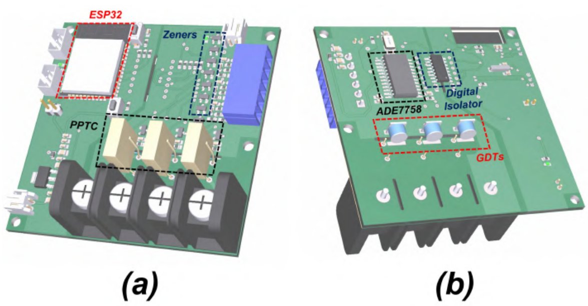


Figure 10. Perspective of the ACU-BREAKER from above (**a**) and below (**b**) in 3D.

5.2.5. ACUs Panel

As mentioned earlier, a panel containing six ACU-BREAKERs, two 5 V power supplies, one for the ESP32-WROOM-32E module's digital circuit and one for the ADE7758's acquisition circuit, and a battery backup were designed. Additionally, a power distribution board was designed and positioned on the panel to share power from the power supplies with the ACUs via connectors. The board was designed to be positioned internally to the distribution board and installed on six of the circuits present. For a total of 48 circuits, eight panels were developed. Figure 11 illustrates the ACU panel previously developed in Inventor software.

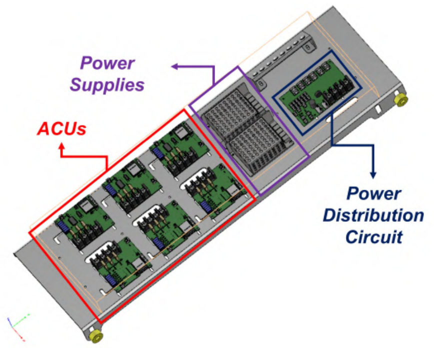


Figure 11. Perspective of the elaborate ACU panel.

5.3. The ACU-ROUTER Middleware

An ACU does not necessarily have to be a hardware device to be developed based on the premises of the SmartLVGrid metamodel. Because it is based on a retrofit strategy, the technological adaptation process can occur through existing devices with the necessary interfaces to enable interoperability with other system applications. In this sense, to interface with the other ACU operators (e.g., ACU-BREAKER) and enable system communication, the ACU-ROUTER (coordinator) was selected to be a wi-fi router in the vicinity of the electrical panel used to implement the proof of concept of this article. The router used was the AP 310 model from Intelbras manufacturer [61].

The wi-fi router does not implement control or monitoring functionality on the electrical circuits or any host system. Therefore, as an ACU, it does not perform DRFs on the host system. However, through it, you can perform message exchanges and communication synchronization with other ACU operators. Thus, through its In/Out port, implemented through its wireless communication transceivers, it was possible to perform ISFs in the system. In addition, this device counts on computational resources for connection management and network configuration, which characterizes its CSFs. For future implementations based on the SmartLVGrid metamodel, it is important to emphasize that the desired operational primitives (DRFs, CSFs and ISFs) depend on the application of ACUs in future systems. Thus, if a market device allows for a non-abrupt technological transition and meets the needs for interfaces to existing/developed systems, it can be used as an ACU. However, for customized solutions, like the ACU-BREAKER, it is necessary to develop the hardware resources and the respective firmware to enable the interaction with other ACUs and the legacy layer, preserving it as much as possible.

5.4. Implementation of the Supervision and Control Center

The supervision and control center was implemented by means of software services and applications, including databases and dashboards, located in a virtual cloud machine on the DigitalOcean [62] provider. Through the SCC, it was possible to view the update of monitored electrical parameters in real time and to register ACUs in order to virtualize the energy monitoring of each circuit in the switchboard.

To develop the screens and dashboards we used the Angular framework in version 10, an open source platform for Web application development [63]. On the other hand, Python language version 3.9 was used to develop software services to transport data to the developed Web application and support the management of other services, such as data storage and device registration. The websocket protocol was used to enable real-time communication between the MQTT broker and the Web application, because through it, it is possible to send requests and receive event-driven responses without the need to consult a server to update the interface [64].

In order to enable the storage of the monitored data in real time, we used the MongoDB database. On the other hand, the event history and device registration were stored in the PostgreSQL database for organization according to data type. Figure 12 illustrates the architecture of the SCC described in this section and its integration with the devices in our proposal.

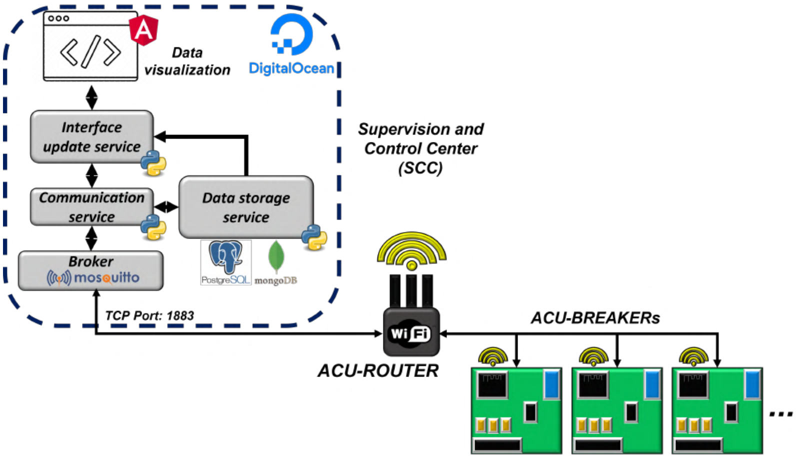


Figure 12. Structure of the supervision and control center.

5.5. Proposal Evaluation Scenario

Our retrofit proposal for monitoring electrical circuits in smart buildings was evaluated in the dental polyclinic of the State University of Amazonas, located in the Cachoeirinha neighborhood, in Manaus. The demands contracted by the distributor are 115 kW during peak hours, from 08:00 pm to 10:59 pm, and 160 kW during off peak hours during the rest of the day. The peak and off-peak tariff schedules for each energy distributor in Brazil can be consulted on the website of the National Agency for Electrical Energy, ANEEL, under "Tariffs and Economic-Financial Information" [65]. Currently, in the case of the polyclinic in question, the electric power distributor is Amazonas Energia.

The polyclinic has an electrical power distribution board, a switchboard, that operates with a nominal voltage of phase-neutral 127 V_{rms}, voltage to which the ACU-BREAKERs were calibrated on the bench. The board in question has 48 circuits and all were monitored by each ACU individually. Each ACU-BREAKER was identified according to the circuit enumeration of the board. The Wi-Fi network configuration parameters, containing the IP address of the virtual machine and the TCP port for MQTT communication, along with the identification of the ACUs, were passed on and stored in the ACUs after the bench calibration procedure. After this, it was possible to assemble the panels with the ACU-BREAKERs, power supplies, batteries, backing plates, and the necessary cabling for installation.

Each ACU-BREAKER was connected to its respective circuit via voltage connectors and current transformers. The panel, in turn, was positioned on the inside of the switchboard. Figure 13 illustrates the ACU panel installed in that scenario. Then, illustrating the retrofit of the switchboard circuits, Figure 14 exposes the ACU-BREAKER connections that interface with the legacy layer of the system. Once powered up, the ACUs, preconfigured with network parameters, began communicating with the MQTT broker running on the virtual machine hosting the SCC applications in the cloud.

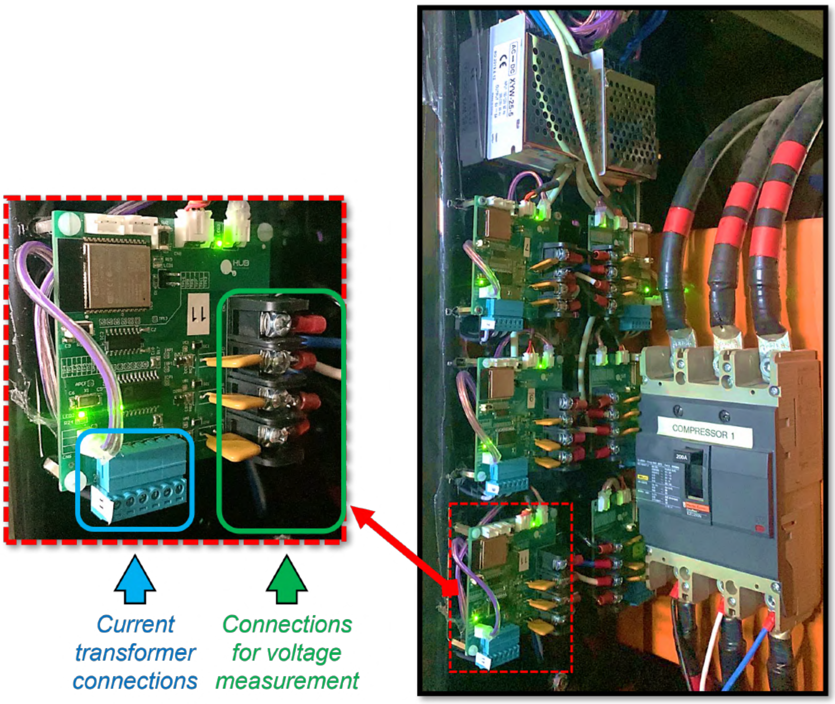


Figure 13. Panel with ACUs installed in the switchboard.

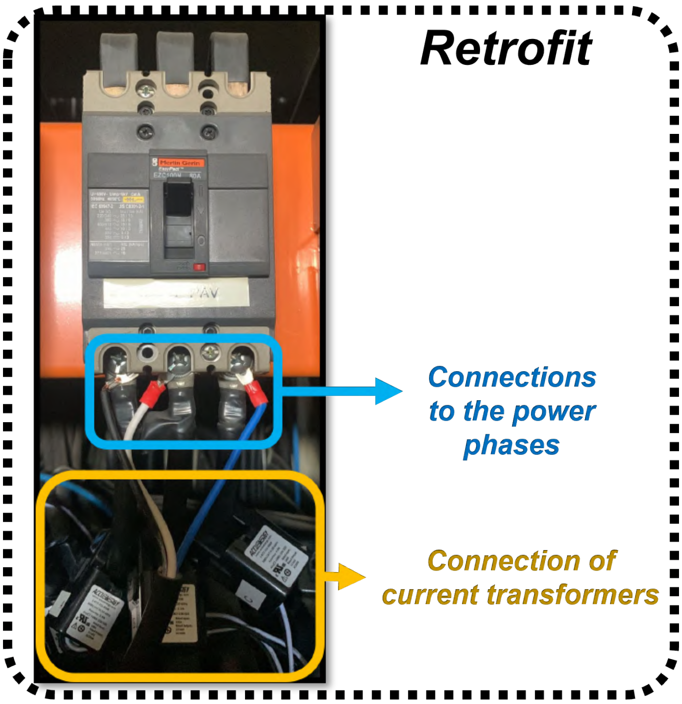


Figure 14. Retrofitting the electrical circuit with ACU-BREAKER connections.

6. Results

In this section, the results obtained from the implementation and performance evaluation of our monitoring proposal for the legacy electric power distribution board will be presented. Initially, the service nodes (SNs) were established by connecting the ACUs to the supervision and control center (SCC) through pre-registered network data. From this, it was possible to evaluate the execution of the operational primitives (DRFs, ISFs, and CSFs) established for the ACU-BREAKER and the ACU-ROUTER, which validates the adaptation of the SmartLVGrid metamodel and the retrofit strategy used. To present the energy management capabilities made available by the proposal, we developed software interfaces that record and expose events and electrical parameters obtained in real time.

6.1. Validation of CSFs

CSFs have been implemented to manage network services and store network configuration data. To illustrate the execution of this operational primitive, Figure 15 exposes some of the logs from the CSF routines implemented in the ACU-BREAKER, obtained by debugging through the universal asynchronous receiver/transmitter (UART) serial interface. In a dual form, these logs also represent the establishment of the network connection made through the LAN interface to the ACU-ROUTER, which in turn establishes communication with the MQTT broker through the Internet.

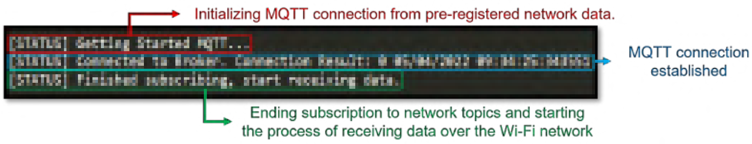


Figure 15. Logs regarding the CSFs implemented in ACU-BREAKER.

6.2. Validation of ISFs and DRF Monitoring of Electrical Parameters

The message exchange process established through the ISFs made it possible to send requests and receive responses between the ACU-BREAKER and the supervision and control center (SCC). This was accomplished via encapsulated packets in JSON format, transmitted via the MQTT protocol with QoS 0. To validate this operational primitive, we captured the sending and receiving data logs from the communication service implemented in Python language in the SCC. From this, it was possible to configure the ACUs, calibrate them, and request the measured electrical parameters of each circuit, characterizing the DRF performed by the ACU-BREAKER. Figure 16 illustrates the logs of the responses of the electrical parameter requests made to the ACU-BREAKER connected to the different circuits of the legacy power distribution board.

Figure 16. Logs of receiving parameters from the switchboard circuits.

It can be seen in the "datetime" field that the electrical parameters were collected at practically the same timestamp, which characterizes the synchronism of the proposed real-time system. In circuit 35, the measured voltages are far below the nominal voltage (127 V_{rms}), indicating an undervoltage event. Note that the voltages of phases A and B of the other circuits are below the nominal voltages, but within the 5% of variation allowed according to the resolution of quality of electric power supply established by ANEEL [66].

6.3. SCC Interfaces

The proposed SCC has the premise of enabling real-time energy management with resources for analysis of power quality and energy efficiency, which is one of the contributions of this work. Its access was accomplished by accrediting users through a login and security key after accessing the address and TCP port of the cloud virtual machine where the application was installed. With the software services in operation, it was necessary to develop interfaces that indicated changes in the power factor, energy demand, monitored electrical quantities and quality of service parameters such as overvoltage and overcurrent [67]. The electrical parameters provide subsidies for the analysis of energy quality, which ensure the reliability of the electrical energy supply service also in low-voltage consumer units [68]. Thus, the importance of this monitoring is justified.

Figure 17 illustrates the interface developed to identify the ACUs in operation associated with each circuit in the frame, including a dashboard to view the instantaneous electrical quantities per phase, the power factor and demand factor, the installed power of the circuit, energy consumption and events related to power quality and energy efficiency. In the "Device Information" field, the unique identification of the ACU in the network (ID) is noted. The consumer unit is also informed, along with the circuit ID (Circuit 32), the installed power and the firmware version of the ACU. There is an indicator as to whether the ACU is connected or not. The field that exposes the occurred events presents the time (timestamp) of occurrence and which event occurred, the value and the percentage of variation of the parameter in relation to the nominal conditions. In Figure 17, the ACU of this circuit has identified consecutive overcurrent events.

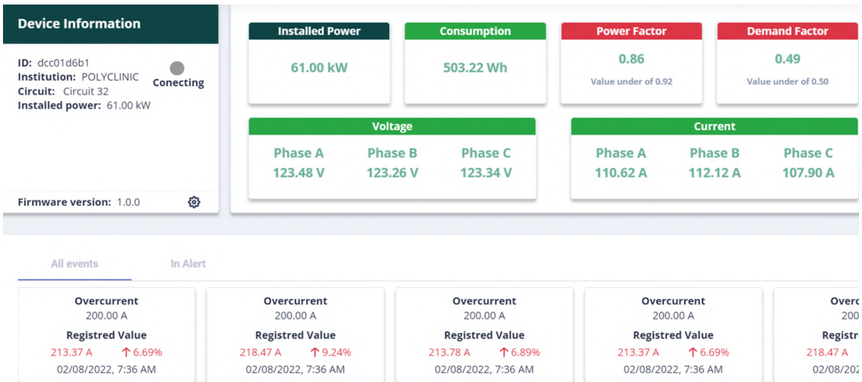


Figure 17. Operational interface for monitoring the circuits via ACUs.

In the dashboard, the cards signal in red the nonconformities with the observed parameters. The demand factor, for example, which represents the ratio of active power measured by the installed power, is below 50%. This value was the threshold set for this metric for analyzing the usage of each circuit in the facility. We established with the building's engineering team that below 50%, the circuit would be underutilized; hence, the definition of this threshold, for this case.

Similarly, Figure 18 exposes the information resulting from the consumer unit, based on the parameters monitored by the ACUs. In the "Consumer Unit Information" field, one can see the consumer unit identification (1780), the consumer unit, and the values of the demands contracted by the utility at peak (115 kW) and off-peak (160 kW) hours. In the dashboard on the side it is possible to view the last registered values of the power factor, active, apparent and reactive power, and energy consumption. According to module 8 of the Brazilian normative resolution ANEEL nº 956/2021, a power factor of the installation below 0.92 results in fines in the energy bill, and this is the threshold for this ratio [66]. In Figures 17 and 18, respectively, it is possible to observe the power factor card of circuit 32 and the installation in red, as they are below the previously defined threshold. In addition, Figure 18 exposes alerts that identify events of exceeding the demand contracted by the utility in off-peak hours, thus events signaling the reduction of the facility's power factor below 0.92.

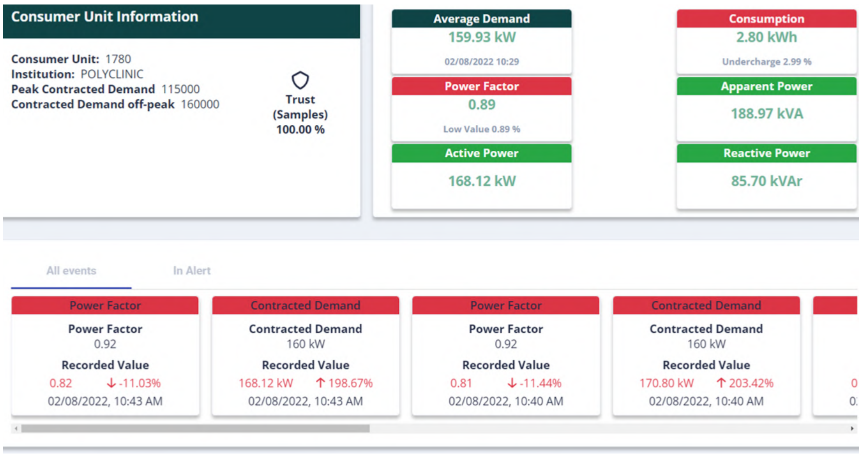


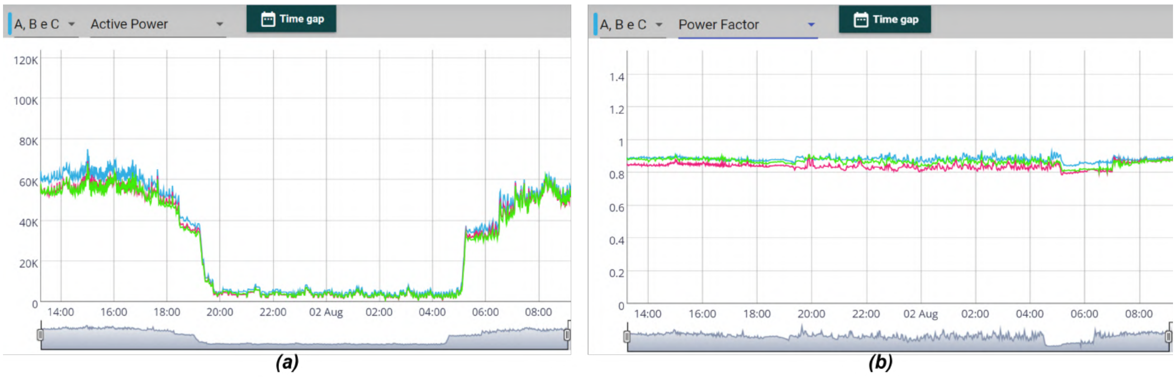
Figure 18. Operational interface for consumer unit analysis.

By using the SCC, it is also possible to observe the time series collected from the ACUs. Figures 19 and 20 expose the active power (a) and the power factor (b) of circuit 47 of the facility and the consumer unit, respectively. Circuit 47 supplies a refrigeration compressor in the installation. In these figures, phases A, B, and C are represented by the curves in blue, red, and green, respectively. The time graphics display up to two monitored electrical quantities per phase or the graphics of the three phases of a single parameter. It should be noted that the viewing history can be selected through the time gap icon and that below the graph the instantaneous values of the quantities are displayed as the cursor is positioned on the screen. In Figures 19 and 20, the visualization period is from 1–2 August 2022.

To visualize the demand and the power factor of the consumer unit with respect to the contract previously established with the utility from the monitored board, we developed differentiated interfaces for analyzing the demand and the power factor. During the same period from 1–2 August 2022, Figures 21 and 22 illustrate the three-phase energy demand and power factor of the installation, respectively. In Figure 21, the three-phase power resulting from the active power of each phase of the consumer unit is observed. As established in the Brazilian normative resolution ANEEL no. 1000/2021, the measured demand must be computed from the average of the three-phase active power every 15 min [69]. Thus, we show in Figure 21 a bar graph to illustrate the demand measured every 15 min of monitoring. We insert the dotted orange curve to represent the demand contracted by the utility at peak and off-peak times. At times when the bar graphs are red, it shows the excess of contracted demand. Otherwise, the graph remains blue. Below the graph, as we position the cursor on the screen, the instantaneous parameters of the graph are shown. On the other hand, Figure 22 shows the installation's power factor, including the limit line that establishes the minimum power factor (0.92).

(a) (b)

Figure 19. Active power (**a**) and power factor (**b**) in each phase (A, B, and C) of circuit 47.



(a) (b)

Figure 20. Active power (**a**) and power factor (**b**) in each phase (A, B, and C) of the consumer unit.

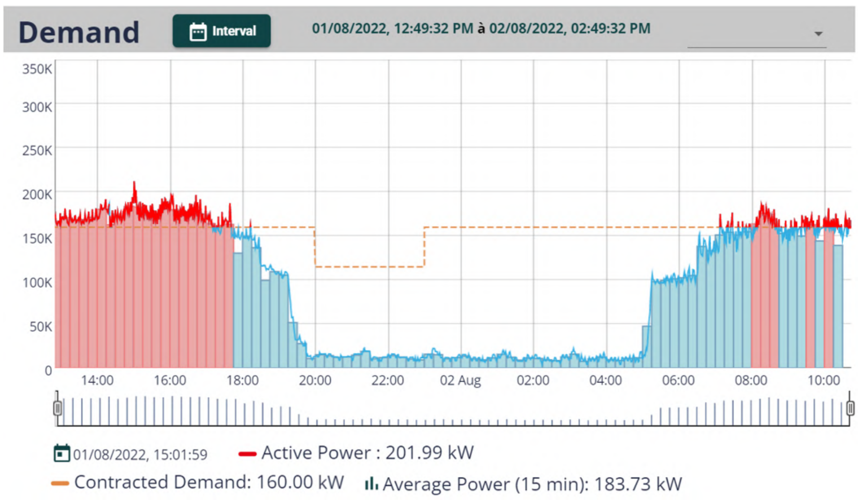


Figure 21. Graph for analyzing the demand of the consumer unit.

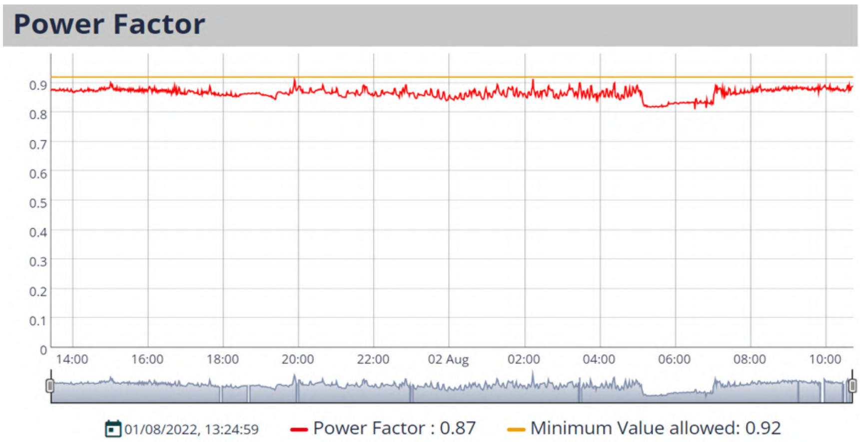


Figure 22. Graph for analyzing the power factor of the consumer unit.

6.4. Case Study with Proposed System

In Brazil, the consumer units can be classified according to the tariff group, according to the contracting options defined by the National Agency of Electric Energy in the Brazilian normative resolution ANEEL nº 1000/2021 [69]. Consumer units of group A are usually medium and high-voltage consumers (industrial, shopping malls, buildings), while consumer units of group B are low-voltage consumers (houses, apartments) [70,71]. Although group B consumer units are charged only for energy consumption, group A consumer units are said to be binomial, and can be charged both for energy consumption and for an energy demand previously contracted with the energy provider [72]. In addition, if the average demand of the 15 min is higher than the contracted demand, the consumer unit will pay a fine for exceeding the demand.

The dental polyclinic of the State University of Amazonas fits in group A and has a contracted off peak demand of 160 kW and peak demand of 115 kW since its inauguration. Currently, the university usually receives monthly increases in its energy bill as a result of excessive energy consumption and excess demand. Subsequently, we identified that since the inauguration, some equipment has been installed in the polyclinic, which has led to increased energy demand. An example of this is circuit 32, which represents the circuit of a compressed air compressor that serves all floors of the facility. Through the ACU-BREAKER responsible for monitoring this circuit, we identified that it is responsible for raising the demand by about 42 kW, approximately 14 kW per phase, as illustrated in Figure 23. In this figure, phases A, B, and C are represented, respectively, by the curves in blue, red, and green.

From our proposal, we identify between May and June 2022 contracted demand exceedances, as shown in Figure 24. It can be observed that at times when the active power is reduced in Figure 23, the demand of the installation is reduced in Figure 24. This way, it can be inferred that circuit 32 is one of the circuits responsible for exceeding the contracted demand in the dental polyclinic facility. Because this circuit supplies an essential load for the activities in the facility, regarding the clinical care of patients, the demand control or equipment replacement are infeasible alternatives at the present moment. In this case, it will be necessary to renegotiate the contracted energy demand, because the initial contracted demand is still being exceeded due to the growth of the polyclinic over the years and the use of energy-intensive equipment. In this way, it is expected that, even with the increase in the contracted demand from the energy concessionaire, the excess fines for exceeding the contracted demand will be reduced, and, with this, the monthly bill. In other words, with the measurements taken from the retrofit strategy implemented in our proposal, it is possible to monitor the energy demand and define actions for the rational use of electricity.

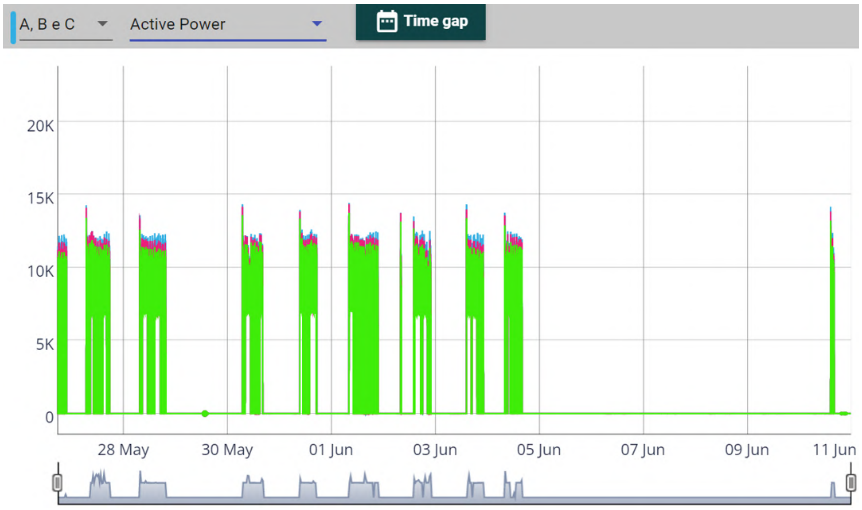


Figure 23. Curve of active powers per phase in circuit 32 of the installation.

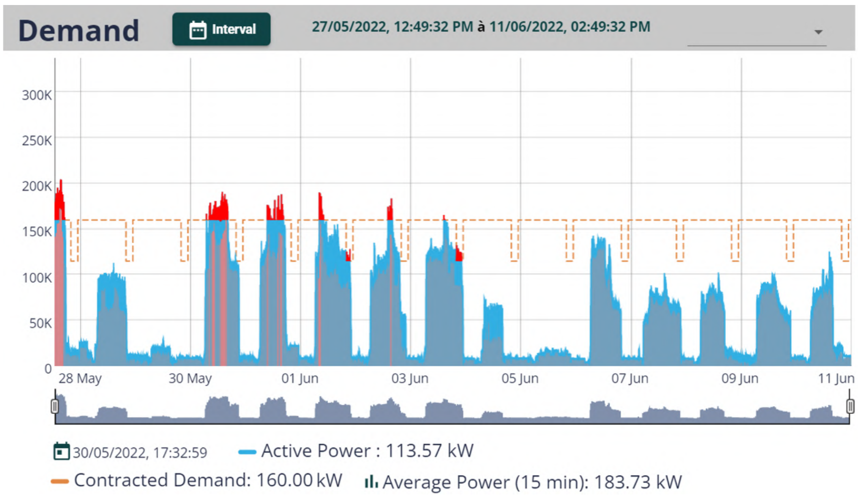


Figure 24. Demand curve for the installation between May and June 2022.

6.5. Discussion

Based on the tests and analysis to validate the retrofit functions and operational primitives of the measurement modules, the conformity of the results with respect to the proposed architecture was noted. Thus, it can be inferred that there was success in adapting the SmartLVGrid metamodel to enable the monitoring interfaces of the electrical circuits of a legacy building installation. It is noteworthy that both ACUs enabled the insertion of remote monitoring resources in a network of devices from the retrofit performed, especially the ACU-BREAKER, which in its operation domain enabled the obtainment of the electrical parameters of each circuit in the grid. Another important validation was the exchange of messages between the supervisory center (SCC) and each ACU-BREAKER, as established in the premises of the interoperability layer.

The parameters monitored by our proposal are of utmost importance for power quality and energy-efficiency studies, because they enable the implementation of energy audit processes to optimize the use of electric energy and reduce costs to the final consumer. In this context, the final consumer can audit and mitigate energy consumption and power quality in a sectored way, analyzing the contribution of each circuit to the increase in energy demand or change in energy quality parameters. With this, the consumer can study the feasibility of contractual changes in energy demand, make changes to the facilities or reduce the use of installed equipment, if possible. Thus, the use of stationary measurement of circuits as proposed in this work is justified. Examples of this were presented in the verification of excess demand and the low power factor of the installation's circuits, as well as of the consumer unit itself. According to the case study shown, the demand of the installation is higher than the contracted demand, suggesting the readjustment of the demand contracted with the concessionaire. It is important to mention that our proposal can be applied to mitigate similar problems in electrical circuits present in large industries and other building facilities, helping managers of these sectors in decision making that lead to significant reductions in energy demand and adequacy of energy quality parameters.

The retrofit strategy used made it possible to take advantage of the entire legacy infrastructure, from the available data network to the electrical materials present in the facility. Despite being a gradual and not-abrupt technological process, the proposed strategy added new resources for building energy management. Considering the deployment of clusters from the proposed architecture, our strategy enables the scalability of the monitoring system as well as the distributed processing of electrical parameters.

The cost of the retrofit carried out in relation to the costs of existing solutions on the market for monitoring building electrical circuits was also analyzed. Initially, before the proposal presented in this work, the maintenance team of the dental polyclinic carried out initial quotations to evaluate the possibility of acquiring devices for monitoring electrical parameters. This survey was conducted through regional and national distributors. At the best quote obtained, each monitoring device was budgeted at about $213.41. In addition, most solutions on the market would not be customized to the needs of the building maintenance team or would take advantage of part of the pre-existing infrastructure in the installation, requiring more resources to operate in the desired way. However, each ACU-BREAKER has a unit production cost of $41.79, not counting the solution development cost (hardware and firmware) and SCC costs. It is known that for large quantities, the cost of the ACU-BREAKER tends to be reduced. Even so, our solution, adapted to the customer's needs, exceeded almost 80% of the cost of the market solution quoted in the region and in Brazil by the maintenance team itself.

The studies found in the literature do not address the use of metamodels based on the retrofit strategy to enable energy management. In addition, most of these studies present specific solutions for pre-established cases, without the use of architectural models that enable the use of legacy infrastructure, in a scalable manner, in order to perform energy monitoring. Furthermore, many of them do not address the reuse of legacy resources. However, the system proposed in this paper distinguishes itself by presenting a method, based on the SmartLVGrid metamodel, dedicated to energy management from the retrofit of legacy low-voltage electrical circuits of a distribution board. More than that, the proposal presents a cloud-based supervisory center, ensuring security and access to data regardless of location, with dashboard capabilities for viewing the history of electrical parameters and events associated with power quality and energy efficiency. Thus, this approach fills a gap observed in the state of the art and technique for energy monitoring, in a systemic and hierarchically well-defined way.

7. Conclusions

In this work, the SmartLVGrid metamodel was used to enable energy management through the monitoring of electrical parameters in real time from the retrofit of the circuits of a legacy switchboard. To do this, an architecture based on the adaptation of the physical and logical interfaces of the original metamodel was proposed so that this new load profile, the circuits of a building installation, could receive new technological functionalities making the most of the pre-existing elements. To validate the strategy presented, it was necessary to develop the hardware and respective firmware of a retrofit module for monitoring electrical quantities, called ACU-BREAKER. This device was assigned operational primitives (DRFs, CSFs, and ISFs), based on the SmartLVGrid metamodel, to execute its functionalities. In order to enable the interconnection of each ACU-BREAKER in a wireless data network, a wi-fi router was used as the system hub, called ACU-ROUTER in the proposed architecture. The ACU-BREAKER and the ACU-ROUTER implement, respectively, the role of operator and coordinator of the proposal. In addition, a cloud-based supervisory system (SCC) was developed to store the monitored parameters and make them available in interactive dashboards for quality and energy efficiency analysis. The monitored parameters were the reactive, active and apparent powers, the power factor, the current and the effective voltage in the three phases of each circuit of the board. Based on the results obtained, it was verified that the proposal enables energy management through a transparent process of technological transition, allowing the maximum use of the available infrastructure of the pre-existing legacy circuits. The proposed architecture is customizable to the installation's needs, because the retrofit can be applied according to the physical and logical interfaces available. In addition, the system's middleware and interoperability layers allow for systemic development and enable distributed processing and scalability for cases of energy monitoring expansion. It is emphasized that, through the results presented, it is possible to mitigate possible excess demand, the reduction of the power factor, and the conformity of the electrical parameters of the installation from the individual analysis of each circuit. In this way, a first step is taken to implement an energy audit process. For future work, we suggest the integration of the proposal of this work with monitoring systems in smart grids and the implementation of clusters based on the proposed architecture, including the analysis of the harmonics present in the system and the evaluation of the performance of the SCC hosted in the cloud with the increase of monitored data. We also suggest the integration and evaluation of our proposal with new dynamic energy markets, involving the apportionment of energy through other alternative energy sources. In addition, with the data collected, it is suggested to label and treat them to predict the demand for energy and other electrical quantities to control the demand of the installation by using electrical drive devices for this purpose. It is also suggested that an economic analysis of the consumer unit through the proposed system be performed.

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Abbreviations

The following abbreviations are used in this manuscript:

ACU	Automation and communication unit
ANEEL	Agência Nacional de Energia Elétrica
BEMS	Building energy management system
CIN	Coupling and interaction nodes
CSFs	Computational support functions
DRFs	Domain retrofitting functions
GDT	Gas discharge tubes
GPIO	General-purpose input–output
IoT	Internet of Things
ISFs	Interdomain support functions
JSON	JavaScript object notation
LAN	Local area network
MAN	Metropolitan area network
MQTT	Message queue telemetry transport
NB-IoT	Narrowband IoT
OPs	Operational primitives
PoI	Points of interface
PTC	Positive temperature coefficient
QoS	Quality of service
rms	Root mean square
SmartLVGrid	Smart Low Voltage Grids
SN	Service node
SoC	System-on-a-chip
SQL	Structured query language
TCP	Transmission control protocol
W	Watts
W3C	World Wide Web Consortium
WSN	Wireless sensor network

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3.3 ARTIGO 02 - A DEMAND FORECASTING STRATEGY BASED ON A RETROFIT ARCHITECTURE FOR REMOTE MONITORING OF LEGACY BUILDING CIRCUITS

3.3.1 Resumo

A previsão de demanda de energia é crucial para planejar e otimizar o uso de recursos energéticos em instalações prediais. No entanto, integrar soluções digitais e técnicas de aprendizagem em edifícios legados apresenta desafios significativos devido aos recursos limitados ou desatualizações, dificultando a análise preditiva nesses edifícios e seus circuitos. Para preencher essa lacuna, este artigo propõe uma estratégia inovadora de previsão de demanda usando uma arquitetura de retrofit AIoT baseada no metamodelo SmartLVGrid. Essa arquitetura permite o monitoramento remoto dos circuitos prediais legados, facilitando a coleta, processamento e armazenamento de dados na nuvem. Usamos vários algoritmos de aprendizado, incluindo regressão linear, regressor de vetor de suporte, regressor de floresta aleatória, regressor XGBoost e redes neurais de memória de curto prazo (LSTM), para prever a demanda de energia 15 minutos à frente, identificando possíveis ultrapassagens de demanda contratada de acordo com os regulamentos brasileiros. Após a otimização bayesiana, a rede neural LSTM superou outros modelos para a maioria dos conjuntos de dados selecionados e detectou 32 de 38 ultrapassagens de demanda no conjunto de teste. XGBoost e floresta aleatória seguiram com bons desempenhos, detectando 30 ultrapassagens de demanda. No geral, nossa solução otimiza o uso de energia e mitiga com eficiência possíveis ultrapassagens de demanda contratada em instalações prediais. Isso foi obtido por meio de uma abordagem sistematizada para atualizar as instalações pré-existentes, promovendo eficiência energética e a sustentabilidade.

3.3.2 Revista

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3.3.3 Corpo Editorial

- Dr. Tullio De Rubeis. Department of Industrial and Information Engineering and Economics (DIIIE). University of LAquila, Italy.
- Dr. Luca Evangelisti. Department of Industrial, Electronic and Mechanical Engineering. Roma TRE University, Italy.

3.3.4 Publicação

sustainability

Article

A Demand Forecasting Strategy Based on a Retrofit Architecture for Remote Monitoring of Legacy Building Circuits

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Abstract: Energy demand forecasting is crucial for planning and optimizing the use of energy resources in building facilities. However, integrating digital solutions and learning techniques into legacy buildings presents significant challenges due to limited or outdated resources, hampering predictive analytics in these buildings and their circuits. To fill this gap, this article proposes an innovative demand forecasting strategy using an AIoT retrofit architecture based on the SmartLVGrid metamodel. This architecture allows remote monitoring of legacy building circuits, facilitating the collection, processing and storage of data in the cloud. We use several learning algorithms, including linear regression, support vector regressor, random forest regressor, XGBoost regressor, and long short-term memory (LSTM) neural network, to predict energy demand 15 min ahead, identifying potential overruns of contracted demand in accordance with Brazilian regulations. After Bayesian optimization, the LSTM neural network outperformed other models for most of the selected datasets and detected 32 out of 38 demand overruns on the test set. XGBoost and random forest followed closely, detecting 30 demand overruns. Overall, our cost-effective solution optimizes energy usage and efficiently mitigates potential demand exceedances in building installations. This is achieved through a step-by-step approach to upgrading existing aging facilities, which promotes energy efficiency and sustainability.

Keywords: demand forecast; retrofit; SmartLVGrid; AIoT; machine learning; real-time energy monitoring; energy efficiency; sustainability; smart buildings

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1. Introduction

Digital paradigms, including internet of things (IoT), and smart buildings and cities, are enabling the efficient use of resources essential for daily activities, such as electricity and water. In addition, they help in better decision making regarding the management of these resources, promoting scalability, flexibility, and dynamism characterized by the so-called data-driven approach [1,2]. However, the digital transformation of legacy systems still presents challenges such as a lack of support and updates, incompatibilities, and insufficient resources to interact with current systems. Alternatively, updating these systems can occur through a process of gradual and less costly technological transformation compared to the complete replacement of legacy systems [3–5]. Thus, using strategies that promote the digital transformation of legacy infrastructures can be a viable alternative for acquiring data and information for data-driven management of legacy systems.

Despite maintaining a significant portion of its legacy resources, the electricity sector is essential for the development of numerous socioeconomic activities. This can be observed by the correlation between the increase in energy demand and the modernization of society [6,7]. Energy demand is a fundamental parameter for issues such as sustainability and energy efficiency, as it subsidizes the dimensioning of energy resources to meet society's needs. However, most legacy systems do not have resources for monitoring or forecasting demand in real time, making it impossible to take actions to reduce or optimize energy demand. Additionally, the lack of these resources makes it impossible to forecast exceedances of the contracted demand of companies and industries with energy concessionaires, which may result in fines or increases in the energy tariff of building installations. Thus, the use of digital solutions to monitor and forecast energy demand represents an opportunity to upgrade and optimize legacy resources.

Artificial intelligence of things (AIoT) can enable the management of electricity in terms of decentralized remote monitoring and computational resources for demand forecasting or energy consumption prediction [8,9]. Nevertheless, the literature lacks demand forecasting strategies based on energy parameters of legacy systems, which in many cases require interoperability resources and real-time monitoring. Without these, accessing the accurate demand profile of existing facilities and their circuits becomes a challenge for forecasting tasks using statistical methods or learning models.

In this context, retrofitting can be a strategy to update existing systems with digital solutions, preserving their resources and infrastructure [10,11]. However, to perform retrofitting systematically, allowing flexibility, scalability, and standardized integration with legacy systems, a reference model with well-defined protocols and interfaces is required. The SmartLVGrid metamodel enables the digital convergence of electrical systems to the smart grids paradigm [3,12]. In the literature, this metamodel has been used to achieve smart building convergence in legacy buildings to promote energy efficiency through resources for managing energy demand and electrical parameters in building installations [4,5].

However, there is a gap in the state of the art regarding the use of statistical techniques and artificial intelligence to predict energy demand in legacy building circuits. In this sense, we propose a legacy circuit retrofitting architecture based on a reference model to monitor electrical circuits and generate a monitoring database that can be used to implement energy demand forecast models for the installation and its circuits. This allows for a systematic and non-abrupt strategy for modernizing existing resources, allowing demand management and forecasting in the operations of building facilities. Furthermore, this proposal may enable the implementation of the strategy in other cases and systems.

In this article, we proposed a demand forecasting strategy in legacy building systems based on the retrofitting of these facilities. In our proposal, we presented a retrofit architecture to integrate hardware devices into a building power distribution panel capable of collecting and transmitting real-time data to the cloud. These data were further processed using supervised learning techniques to predict the energy demand of both the facility and its circuits. We used the SmartLVGrid metamodel at the physical and architectural levels as a basis to retrofit the legacy installation, ensuring the necessary interfaces and interoperability between monitoring devices and the cloud application created for data storage and processing.

With the data acquired by the proposed monitoring system, we conducted an exploratory analysis of the consumption and demand data from the installation and its circuits to mitigate the potential exceedance of the contracted demand in the legacy building installation of this study, following the regulatory standards for energy supply and distribution in Brazil, where the proposal was validated. Consequently, we performed short-term demand forecasting for the next 15 min. As learning models, we employed the random forest regressor (RFR), support vector regression (SVR), XGBoost regressor (XGBR), and a long short-term memory (LSTM)-based neural network architecture. Additionally, we used the performance results of the linear regression (LR) model as a baseline for evaluating and comparing the performance metrics (root mean squared error—RMSE, mean absolute error—MAE, and R-squared score—R^2) obtained for the mentioned models.

Therefore, we highlight the following contributions of this work:

(1) Developing an AIoT solution for energy demand forecasting in legacy buildings and their circuits based on a retrofit strategy;
(2) Implementing and comparing the performance of demand forecasting models in legacy electrical circuits using different learning models;
(3) Implementing a new real-time monitoring system for energy demand in legacy electrical circuits based on the SmartLVGrid metamodel;
(4) Proposing a systematic method for creating databases through the monitoring of pre-existing circuits;
(5) Developing an alternative for detecting exceedances of the contracted demand with energy utility companies in legacy building installations using learning models.

To present our proposal, we divide the paper as follows: Section 2 provides a survey of the state of the art related to the topic. In Section 3, we highlight the research gaps in the literature concerning the theme of this work. Section 4 provides the theoretical framework of the SmartLVGrid metamodel. Section 5 presents our proposal for energy monitoring based on retrofitting low-voltage legacy circuits of a power distribution panel. In Section 6, we define our strategy and methodology to enable demand forecasting in the building installation and its legacy circuits. Section 7 presents the obtained results. In Section 8, we discuss the results, followed by the conclusions and proposals for future work in Section 9.

2. Related Work

The forecasting of energy demand is constantly researched in the literature, as well as the prediction of energy consumption. Among the approaches used in this context, statistical methods, machine learning, or deep learning models can be mentioned, employed based on pre-established databases. The most commonly used statistical methods are based on autoregressive techniques, with the most common ones being autoregressive integrated moving average (ARIMA) and seasonal ARIMA (SARIMA) methods. In [13], the SARIMA method was used by the authors to predict energy consumption in Poland on a quarterly, monthly, and weekly scale, using data from 2015 to 2021. In [14], the authors used the ARIMA method to estimate energy demand in Brazil from 2021 to 2025 and evaluated the predictability of the model using real data from the period 2014 to 2015. The authors of [15] also employed the SARIMA method to forecast short-term energy consumption for the Brazilian industrial sector. These statistical methods have also been used in the literature to make predictions using time series by rearranging the data present in the datasets to enable the forecasting of future energy demand based on past demand values. In the works [16,17], the authors used the sliding window method and autoregressive models to enable predictions of short-term future demands.

Although statistical methods have shown significant results in time series forecasting, they are well-suited when the dataset exhibits well-defined seasonality and trend patterns. When the time series exhibits more complex and even nonlinear patterns, machine learning methods can provide better results compared to statistical methods [18]. In [19], the authors proposed models for predicting electricity consumption in Slovakia using artificial neural networks. The authors of [20] used the support vector regression (SVR) and generalized regression neural network (GRNN) models to predict energy consumption in Indonesia. In the work [21], the authors applied random forest regression (RFR) and SVR to predict medium-term electricity demand using a Canadian database. In [22], the authors applied two ensemble learning methods, the XGBoost regressor and RFR, to forecast demand for the next day during the pandemic period. In the work [23], the authors employed machine learning methods, including linear regression (LR), multivariate polynomial regression, SVR, gradient boosting regressor (GBR), RFR, and K-neighbors regressor, to predict energy demand in New South Wales, Australia. In [24], the authors developed a clustering-based method for electricity prediction that was evaluated using a dataset with data from 105 substations. In the work [25], the authors presented a summary of the works developed in the IEEE demand forecasting competition, which included anomalous consumption data from a metropolitan region during the COVID-19 pandemic period. Various data preprocessing and demand prediction methods using machine learning were presented. In an analysis of the cited works, it is mentioned that in cases of large data volume, nonlinear relationships among the characteristics present in the database, the presence of noise, and non-stationary behaviors, deep neural networks can be an alternative to machine learning. However, it is emphasized that deep networks require more computational resources and are more complex compared to supervised machine learning models. It is also mentioned that authors commonly use recurrent neural networks in this scenario, especially LSTM networks, combined with sliding window techniques [26–31]. Tables 1 and 2 summarize the previously presented works.

Table 1. Studies employing statistical methods for demand and energy consumption prediction.

Work	Year	Application	Methods or Models	Dataset Origin
[13]	2021	Prediction of electricity consumption in Poland on a quarterly, monthly, and semi-annual scale.	XGBoost, GRNN, SARIMA, ETS, NNETAR	Cire.pl
[14]	2022	Forecast of Brazilian monthly energy demand.	RS, ES, ARIMA	ONS Brazil
[15]	2022	Prediction of monthly consumption of industrial electricity in the Brazilian energy system.	HW, SARIMA, TBATS, DLM, NNAR, MLP	Central Bank of Brazil
[16]	2022	Out-of-sample, monthly, weekly, and hourly forecast for Nord Pool electricity demand.	AR, FAR, FARX	Nord Pool
[17]	2022	Short-term forecast of hourly energy demand of different energy districts.	SLFN, ARIMA, SVR, LSTM	Arpae, ARPA Lombardia

The abbreviations are presented in the list of abbreviations.

Table 2. Machine and deep learning studies for demand and energy consumption prediction.

Work	Year	Application	Methods or Models	Dataset Origin
[19]	2022	Development of electricity forecasting models in Slovakia.	Gray Models, ANN	Damas (SEPS)
[20]	2022	Electricity prediction in Bali Island, located in Indonesia, using electricity and weather data.	SVR, GRNN	East Java Province, domestic generators, ERA5-ECMWF
[21]	2021	Use of machine and deep learning models for medium-term prediction in Canada.	LSTM, SVR, NARX, RFR	IESO (Canada), Gov. of Canada
[22]	2022	Forecast for the next day of energy demand in Germany in COVID-19 pandemic period.	Ensemble-based models	OPSD
[23]	2022	Prediction of energy demand in New South Wales, Australia.	LR, MPR, SVR, ENR, GBR, DTR, RFR, KNNR	AEMO, Gov. of Australia
[24]	2022	Energy prediction based on cluster optimization method.	Greedy clustering	Ausgrid
[25]	2022	Demand prediction works in a metropolitan region using machine learning, statistical methods, and hybrid models.	Ensemble methods, AR, LR	BluWave-ai
[26]	2022	Short-term energy forecast using learning models.	ARIMA, LSTM, Prophet, Hybrid models	Elia grid
[27]	2020	Long-term demand prediction in Florida with regression models.	MRM, CNN variants, RFR, LSTM	EIA (U.S.), FCC, Census Bureau (U.S.), Bureau of Labor Statistics (U.S.)
[28]	2022	Prediction of energy consumption in Spain using LSTM networks.	LSTM variants	Spain Electricity Consumption
[29]	2021	Use of LSTM and convolutional networks for short-term demand forecasting in France and Korea.	LSTM and CNN variants	UCI repository, local Korean dataset
[30]	2023	Forecasting energy consumption demand using TFT, which outperformed other deep learning models.	LSTM variants, TCN, TFT	London DataStore
[31]	2022	Energy consumption forecasting on smart grids with N-BEATS, outperforming other deep learning methods.	LSTM and GRU variants, TCN, N-BEATS	London DataStore

The abbreviations are presented in the list of abbreviations.

The previously cited works contribute to the state of the art in demand forecasting and energy consumption. However, these works focus on predictions and forecasts relevant to energy companies, regional, or national contexts, rather than being directly related to building and industrial facilities. Additionally, the datasets employed were not produced through wireless sensor networks (WSNs) developed and configured by the authors, which would allow for the investigation of specific details or aspects, such as the use of predictive models for energy demand control, for example.

Thus, we sought literature that investigates the building context and applications of demand forecasting specifically tailored to building installations. In [32], demand and generation prediction of renewable energy sources, specifically photovoltaic and wind energy, were conducted in five smart residences using LSTM networks as prediction models, with approximately 11 months of collected data. In [33], an energy management strategy based on demand classification and prediction was presented. In addition to predicting the demand for a commercial building in Singapore, the authors developed neural network algorithms for decision making regarding energy excess treatment, application of photovoltaic energy, and energy storage conditions in the battery bank. In [34], the authors used a FFANN model for demand forecasting in the next 24 h for residential, educational, and mixed-use buildings. The authors of [35] predicted energy consumption in a food company based on data obtained from the factory's energy management system using the SVR and multilayer perceptron (MLP) methods. The work in [36] presents a study to assist managers and technicians with long-term energy predictions for a building at Teesside University (UK) using different machine learning techniques such as SVR and neural networks. In [37], the authors performed demand prediction using LSTM networks applied to the context of smart buildings. In [38], energy consumption data from smart meters installed in building substations, which recorded the consumption of the entire building at 15-mi intervals, were utilized. Based on this data, the authors analyzed the integration of methods for consumption forecasting to improve energy efficiency in building installations. Table 3 presents the works cited in this paragraph on demand forecasting and energy consumption in building and industrial infrastructures.

Table 3. Research on forecasting demand and consumption of electricity in building and industrial infrastructures.

Work	Year	Application	Methods or Models	Dataset Origin
[32]	2021	Energy prediction and for renewable sources in smart buildings.	LSTM variants	HUE dataset (Havard dataverse)
[33]	2020	Prediction and classification of energy demand for decision making in smart buildings.	MLP, RNN, LSTM, GRU, EM-GMM, BGM, K-means	Own data
[34]	2019	Use of the FFANN model to forecast demand for the next 24 h of buildings.	FFANN	Buildings of Finland
[35]	2023	Energy prediction in a food company using machine learning models.	MLP and SVR variants	Own data, KEPCO, KMA
[36]	2021	Long-term energy prediction in a university building.	PR, SVR, ANN	Own data
[37]	2022	Prediction of energy demand in smart buildings.	ARIMA, LSTM	Mendeley data
[38]	2022	Forecasting of energy consumption in smart buildings with different drift detection methods.	RFR, XGBoost CNN, TCN	Own data

The abbreviations are presented in the list of abbreviations.

Additionally, we selected some works that incorporate the concept of AIoT for electrical energy analysis. In [39], the authors developed a hardware device to monitor human presence and energy consumption. By using a decision tree model on a cloud-stored database, they determined energy waste in residential consumer units. Using the same decision tree algorithm, the authors of [40] created an energy control system based on hardware with wifi communication, relays, current sensors, and cloud storage. In the work [41], neural networks were employed to predict energy consumption based on data collected from sensors in a residential system. The authors utilized these predictions to turn off one or more devices to reduce monthly energy consumption. The authors of [42] addressed the challenges of thermal management in electric vehicle batteries and proposed an AIoT-based preventive diagnostic system to improve safe driving, efficient maintenance, and product lifecycle management, aiming to optimize efficiency and battery life. Table 4 summarizes the selected AIoT works.

Table 4. Literature works on AIoT implementation in energy applications.

Work	Year	Application	Methods or Models	Dataset Origin
[39]	2022	IoT solution to control consumption and energy waste in homes.	Decision tree	Own data
[40]	2021	AIoT solution for controlling energy consumption in smart homes.	Decision tree	Own data
[41]	2022	Use of neural networks to control energy consumption in homes from wireless sensor networks (WSNs).	ANN	Own data
[42]	2023	AIoT system for preventive diagnosis of thermal challenges in electric vehicle batteries.	ANN	Own data

The abbreviations are presented in the list of abbreviations.

3. Research Gap

Previous studies on demand and energy consumption forecasting have shown the potential to enhance energy efficiency in building and industrial infrastructures within their respective contexts. However, there are several gaps in the current state of the art regarding demand or energy consumption forecasting in building facilities:

- Most existing studies rely on databases generated by third parties, without real-time AIoT solutions specifically designed to construct databases that capture patterns or characteristics of not only the overall electrical installation but also individual circuits and sectors within it. This presents an opportunity to leverage demand or consumption forecasting algorithms to optimize operations for specific installations of interest;
- The studies have not explored the forecasting of energy consumption and demand at the circuit level within building installations, which would enable individual analysis of high-consumption loads within the facility. This limitation stems from the lack of digital monitoring solutions that can collect individual demand data from building circuits, in addition to capturing the overall energy demand of the facility;
- The existing works do not provide AIoT solutions that enable the forecasting or detection of demand exceedances in legacy building systems, hindering digital convergence in pre-existing environments. A sustainable technological alternative is needed to promote energy efficiency in these installations. Retrofit strategies could be employed to introduce computational resources and update legacy infrastructures, leveraging existing resources to extract consumption and energy demand data for specific studies focused on legacy installations;
- The studies do not utilize retrofit strategies or metamodels with generic architectures and protocol stacks to enable systematic data collection through digital solutions that incorporate control, monitoring, distributed processing, and communication capabilities within data networks. Such approaches would benefit various cases and applications in the domain of energy forecasting.

Therefore, this study proposes to address these gaps by developing and implementing digital solutions using retrofit techniques and the SmartLVGrid metamodel for accurate demand forecasting in legacy installations.

4. SmartLVGrid

A smart low-voltage grid, or SmartLVGrid, is a metamodel that enables the technological convergence of legacy power distribution systems into the smart grid paradigm through retrofit strategies and systems engineering concepts. Its proposal involves adding electronic and computational resources for the control and monitoring of legacy systems using supervisory systems hosted on a local network or even in the cloud. These functionalities are described in the platform as operational primitives (OPs), which were previously performed by field operators and later, with the implementation of the metamodel, taken over by the added technological resources. This metamodel consists of protocol stacks described in two layers: middleware and interoperability, as shown in Figure 1.

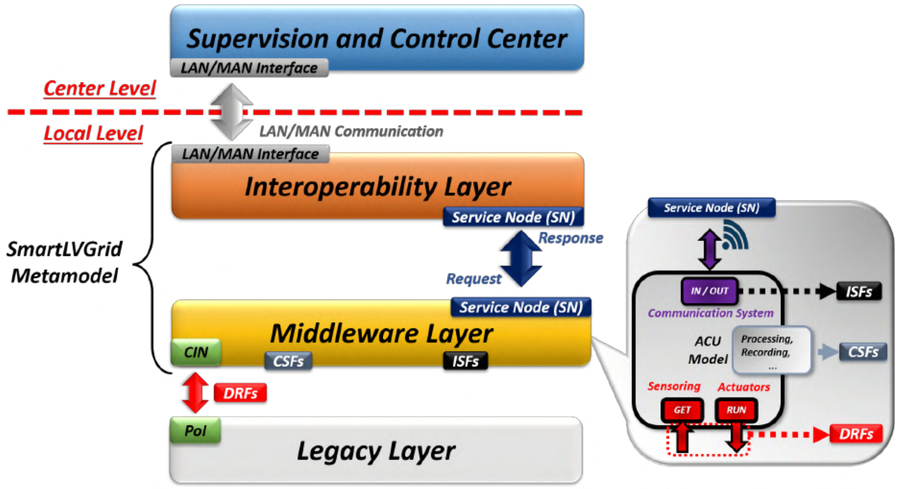

Figure 1. The SmartLVGrid stack [4].

As illustrated in Figure 1, the retrofitting of the existing infrastructure (legacy layer) is carried out through points of interface (PoIs) that interact with the middleware layer through the coupling and interaction node (CIN). Through this interface, the metamodel defines one of its operational primitives (OPs) called the domain retrofitting function (DRF), which is responsible for performing control and monitoring functions in the legacy layer. On the other hand, the service nodes (SNs) enable the middleware layer to interact with the interoperability layer through predefined communication standards and protocols. Thus, communication processes are performed by the interdomain support functions (ISFs). It should be noted that in the middleware layer, computational support functions (CSFs) are implemented to provide processing and storage services. In the following paragraphs and Sections 4.1 and 4.2, more details about the middleware and interoperability layers will be provided.

4.1. Middleware Layer

The middleware layer, which interacts directly with the legacy layer, is implemented through retrofitting solutions. Typically, these solutions encompass hardware devices with embedded processing, including sensor and actuator elements compatible with the DRFs to be executed. Alternatively, the middleware layer is described as the automation and communication unit (ACU), as shown in Figure 1. The ACU has "In/Out" ports that perform the communication processes, "Get" and "Run", responsible for monitoring functionalities and controlling the legacy system, respectively. It should be noted that the CSFs are executed through the storage and processing resources of the ACU.

4.2. Interoperability Layer

The interoperability layer enables communication between ACUs through a data network. Additionally, the communication protocols and device hierarchies modeled through the SmartLVGrid metamodel are established within the interoperability layer. In this context, the ACUs that supervise and collect data from other ACUs, as well as execute DRFs when applicable, are hierarchically referred to as ACU coordinators. On the other hand, the supervised ACUs that execute DRFs in the legacy layer are called ACU operators. In cases of expanding the legacy system, it may be necessary to increase the computational capacity of the ACU coordinator. In the metamodel, it is possible to define sub-coordinators for each cluster of ACU operators, as described in [4]. Thus, sub-coordinators are associated with a single ACU coordinator, which transfers system information to and from the supervisory center. It is important to emphasize that, due to the local processing capability of each ACU, actions and directives can be performed by the ACU itself at the local level, enabling distributed and decentralized processing.

5. Methodology for Implementing the Energy Monitoring System

In previous works, we utilized wifi network infrastructures for communication with the supervisory centers [3–5]. However, in this study, we explore a different alternative for communication between our monitoring proposal and the supervisory center, as well as for the physical interface of the retrofit modules with the legacy building circuits, considering the specific characteristics of the monitored consumer unit. Specifically, we focus on a wifi router assembly factory where the main power distribution panel does not have sufficient space for installing retrofit modules, as shown in [5]. In this scenario, it is a factory regulation not to use wifi networks within its facilities to reduce interference issues and IP node conflicts during router testing and validation processes. Therefore, we employ a different retrofit approach compared to previous state-of-the-art works in terms of both physical and logical interfaces. Figure 2 illustrates the proposed retrofit strategy for the power distribution panel in the industry under study. Subsequently, Figure 3 presents an architecture diagram of the devices used in accordance with the SmartLVGrid metamodel, highlighting the adopted communication standards as well as the physical and logical interfaces of our monitoring proposal.

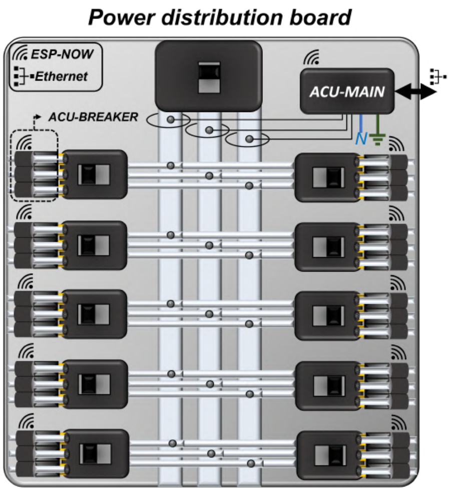

Figure 2. Retrofit strategy.

As depicted in Figure 2, the new strategy involves the integration of more compact retrofit modules compared to the modules developed in [5]. Still referred to as ACU-BREAKERs, in this study, the retrofit modules were powered by connecting them to the breakers of the main power distribution panel, enabling the monitoring of electrical parameters for each circuit. This made individual circuit monitoring more independent as we utilized non-shared power sources for each retrofit module. On the other hand, the proposed approach included an ACU coordinator with the capability to: (i) communicate with the ACU-BREAKERs and the supervisory and control center (SCC); (ii) provide backup power through batteries; and (iii) monitor the electrical parameters of the main panel breaker. This device was named ACU-MAIN. It is worth noting that the current measurement of both ACU-BREAKER and ACU-MAIN were performed non-invasively using current transformers, and voltage was measured through direct contact with the terminals of the breaker and the main power bus.

In this study, we employed a technological update approach based on the protocol stack of the SmartLVGrid metamodel, and we conceptualized the physical and logical interfaces of the devices as presented in Figure 3. In this figure, we illustrate the peer-to-peer communication between the operator modules, the ACU-BREAKERs, and the coordinator module, ACU-MAIN, to forward the acquired data from the monitored circuits and the main panel breaker to a local server. It is important to highlight that the monitoring of the main breaker was not performed in [5], a feature that enables the detection of power supply interruptions in other monitored circuits of the installation.

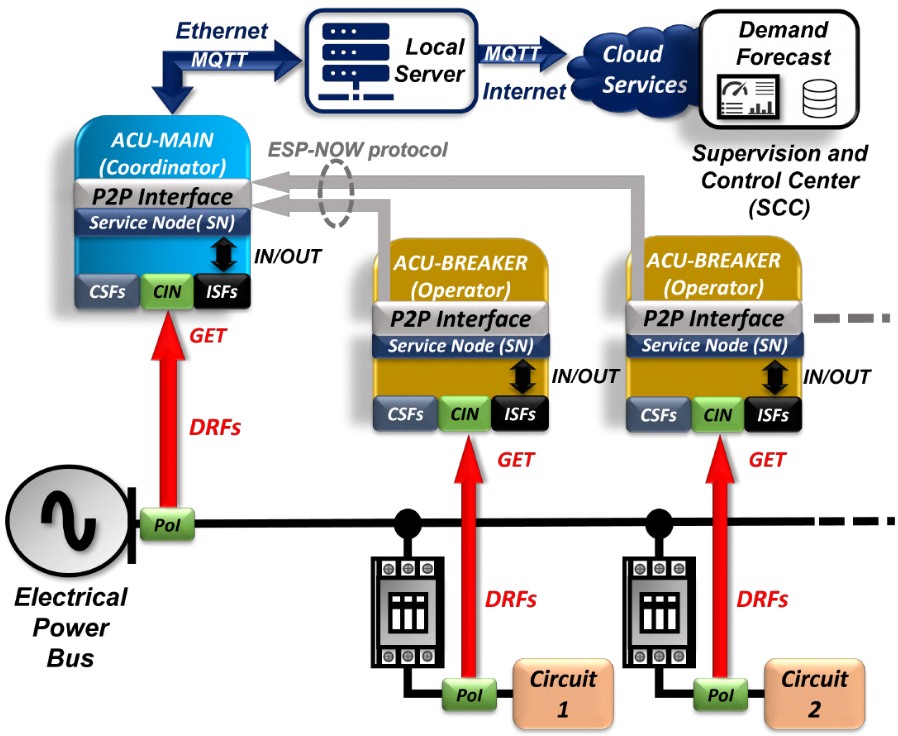

Figure 3. Proposed SmartLVGrid architecture.

To avoid the use of a wifi infrastructure network for communication between the ACU operators and the ACU-MAIN in the mentioned industrial environment, we employed the ESP-NOW ad hoc low-level network, which enables multi-hop, lightweight, secure, self-organized wireless communication. ESP-NOW operates in the 2.4 GHz ISM band and can coexist with other standards such as Bluetooth and wifi [43,44]. Studies have shown that ESP-NOW exhibits lower latency and longer range compared to Bluetooth and wifi [45]. Additionally, unlike Bluetooth low energy, ESP-NOW does not limit the number of connected nodes, which justified its selection as the network protocol for peer-to-peer interconnection [46]. On the other hand, the logical interface between the

ACU-MAIN and the supervisory center was established through wired communication with a local server, adopting the MQTT protocol over ethernet. This allowed us to establish a connection with the cloud-hosted SCC. In summary, some benefits related to the hardware and communication architecture of our retrofit proposal include:

- Utilization of a peer-to-peer communication architecture among the wireless nodes, ACU-BREAKER (operator), and ACU-MAIN (coordinator), through the ESP-NOW ad hoc network, enabling communication flexibility and reducing the number of IP nodes;
- Adaptation of the monitoring modules, ACU-BREAKER, with a specific and compact design for installation in small-sized power distribution panels, reducing the space requirements and visual clutter of the industrial distribution panel;
- Development of retrofit modules that allow easy and intuitive installation in power distribution panels, thanks to the agile coupling features and reduced physical dimensions;
- Preservation of the existing resources in the installation, including the infrastructure, breakers, cables, connections, and the main distribution panel itself.

In this way, we enable the monitoring of the electrical panel and the forwarding of data to a local server for subsequent transmission to the cloud, where the supervisory and control center (SCC) is located. In the SCC, we built a dataset containing the obtained data from each circuit to be used in the demand prediction algorithms. Expanding its original proposal, the SCC now contributes not only with resources for storing and visualizing past information but also with predictive analysis resources for each circuit of the building installation through demand forecasting. The retrofit proposal tests were carried out by integrating and validating the physical integration and communication of the monitoring system with the cloud application, which receives the electrical parameters obtained from each circuit.

Subsequently, we present the modeling of the ACUs, compatible with the assumptions of the SmartLVGrid metamodel. The presented modeling will provide a detailed understanding of the conceived and developed physical and logical interfaces at the hardware and/or software level for the retrofit modules in the energy monitoring system.

5.1. ACU-BREAKER Conception and Modeling

Figure 4 presents the improved ACU-BREAKER (operator) developed during this work. The main differentiators of this ACU operator are its physical connection to the legacy circuits of the power distribution panel and the use of the ESP-NOW ad hoc protocol for communication between the ACU operators and the coordinator. As shown in the figure, it has metallic terminations that fit into the breakers and current transformers embedded in its structure. Therefore, the installation of the ACU-BREAKER is facilitated by inserting and screwing the connection cables of transformers/breakers onto the metallic terminations of the ACU-BREAKER. It is worth noting that the hardware and firmware resources and functionalities of the ACU-BREAKER are similar to those described in [5]. Thus, this ACU provides the DRF of electrical parameter monitoring through its Get port, performs ISFs of request and response through its In/Out port, and utilizes the ESP-NOW protocol for communication, along with CSFs related to network connection management, device configuration, and data storage. In terms of hardware, this device includes the same electronic surge protection devices, voltage and current channel conditioning, and ADE7758 for digitalization of acquired electrical parameters [47–49]. It is important to mention that the calibration procedures for the ACU-BREAKER, as described in [5], were maintained during the development of this work.

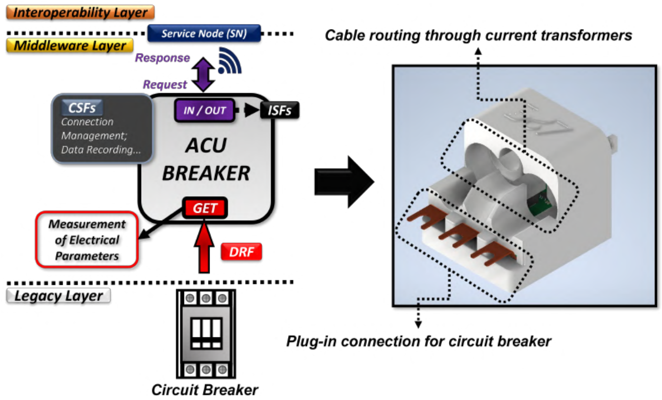

Figure 4. ACU-BREAKER architecture diagram and its physical perspective after development.

5.2. ACU-MAIN Conception and Modeling

The ACU-MAIN coordinator of the proposed system has similar DRFs, ISFs, and CSFs as the ACU-BREAKER. Additionally, it has the function of managing the network connection and communication with the other ACUs, including storing the identification data of the connected ACUs. Furthermore, it has an ethernet communication interface to communicate with the local server of the factory using the MQTT protocol [50–52]. The service nodes (SNs) of the SmartLVGrid metamodel for both the ACU-MAIN and ACU-BREAKER are established based on the credentials used in the ESP-NOW communication protocol, which includes the MAC address of the ESP32 used in the ACU hardware. It should be emphasized that the In/Out ports of this ACU are implemented through the ethernet interface for MQTT communication and the 2.4 GHz radio for ESP-NOW communication. The voltage and current parameters are monitored through the physical connection to the main bus and current transformers, respectively [53]. Figure 5 illustrates the ACU-MAIN developed in this work.

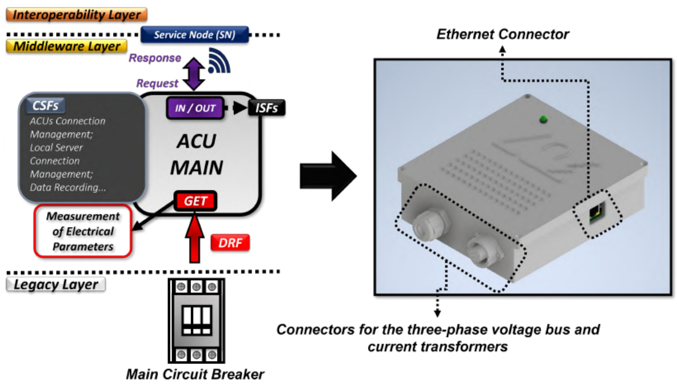

Figure 5. ACU-MAIN architecture diagram and its physical perspective after development.

5.3. Definition of the System Interoperability Layer

As mentioned earlier, the interoperability of the system occurs through two forms of communication. First, within the power distribution panel, the ACU operators communicate with the ACU-MAIN using the ESP-NOW wireless communication protocol. Second, the ACU-MAIN communicates with the local server of the factory through an ethernet interface, using the MQTT protocol with QoS 0. It should be noted that the ethernet interface was determined according to the company's requirements and aligns with the retrofit concept of the SmartLVGrid metamodel, which aims to maximize the utilization of the existing legacy system. Consequently, the local server forwards the messages to an MQTT broker hosted on the DigitalOcean Droplet virtual server hosting service, also with QoS 0, where the processing of energy data takes place. It is important to mention that the request messages for electrical parameters are transmitted in JSON format and, upon receipt at the SCC, they are stored in a MongoDB database.

The service nodes (SNs), illustrated in Figures 4 and 5, represent the credentials that allow the ACUs to communicate in a wireless network. In this work, the SNs are implemented through the credentials that enable the communication of devices using the ESP-NOW protocol, including the MAC address of the ESP32 in each ACU in the proposed P2P interface.

Regarding the messages in our proposal, they are implemented using JSON format for both the interface between ACU operators and the ACU-MAIN and the interface between the ACU-MAIN and the local server. The same message protocol is also adopted for communication between the local server and the SCC. The messages include request and response messages for sending the monitored electrical parameters along with timestamps, network communication parameter changes, inclusion of new devices, and ACU-BREAKER calibration. Figure 6 illustrates the process adopted to enable the interoperability of our proposal in a request of electrical parameter scenario as follows:

- The local server requests the electrical parameters from the ACU operators and the ACU-MAIN every minute (1);
- The configuration of the service nodes (SNs) of the ACU-BREAKERs and the ACU-MAIN is performed (2);
- The request for electrical parameters is sent from the ACU-MAIN to each ACU-BREAKER using the ESP-NOW protocol (3);
- Upon receiving the request, the ACU-BREAKER performs ISFs to synchronize communication and transmits the requested data to the ACU-MAIN (4);
- After collecting the information from the ACUs and the message timestamps, the local server forwards the data to the cloud-hosted SCC (5).

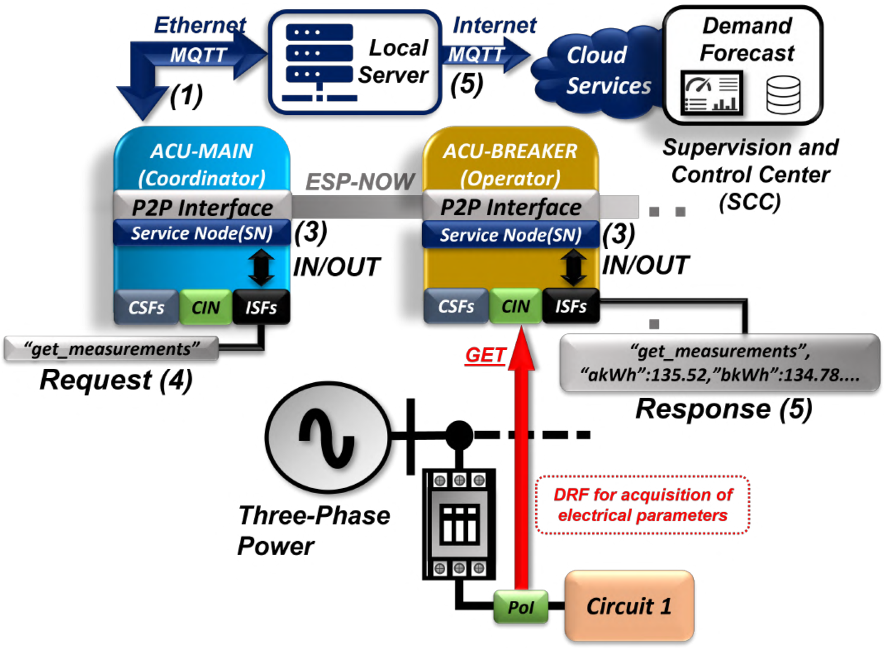

Figure 6. Communication process of the proposed system.

5.4. Installation of the ACUs

Once assembled, tested, and calibrated, the ACUs were installed and configured to operate in the existing power distribution panel of the router factory. Each ACU was calibrated beforehand to match the nominal currents and voltages of the breakers in the panel, with a maximum error of 1%, using a precision three-phase source and the internal registers of the ADE7758, the integrated circuit used in the ACUs for electrical parameter digitalization [54,55]. The panel operates with a phase-neutral voltage of 127 V_{rms} and has 22 circuits. Figure 7 illustrates the ACUs installed in the legacy power distribution panel. As depicted, the first distribution breaker does not have an ACU-BREAKER installed, as it was damaged during the evaluation period of the proposal.

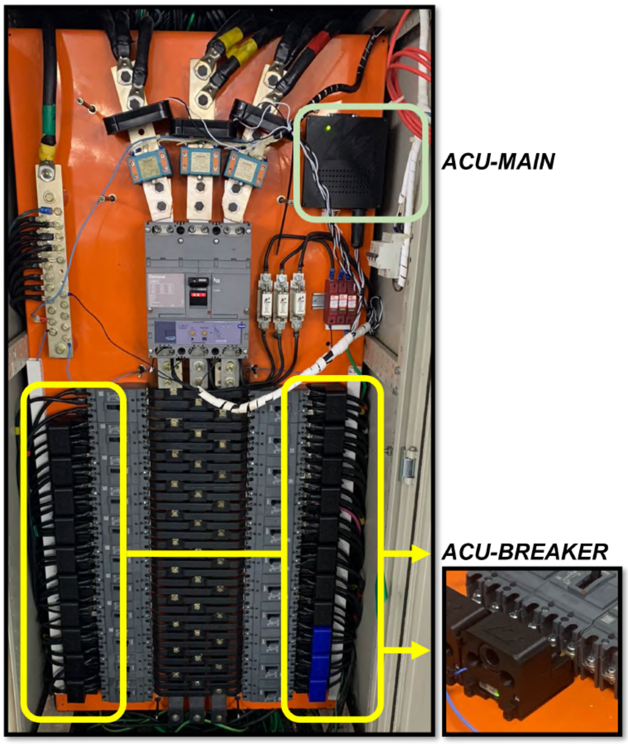

Figure 7. ACUs installed on legacy power distribution board.

6. Proposed Demand Forecast Strategy

The literature presents applications of the SmartLVGrid metamodel used for the management, control, and energy monitoring of power distribution systems and building systems [3,4,12]. In [5], we presented a data-driven energy management strategy by monitoring real-time energy demand in each circuit of a building installation based on the aforementioned metamodel. In Brazil, where the proposed work was implemented, medium- and high-voltage consumer units are categorized as "binomials", being charged based on both consumption and previously contracted energy demand from a local energy distributor [56]. The demand is weighted every 15 min, and if it exceeds the stipulated value in the established contract, the consumer unit is subject to fines according to the Brazilian National Electric Energy Agency (ANEEL) in the normative resolution ANEEL No. 1000/2021 [57]. To assist the participating managers in the conducted case study, we also developed a visual interface with demand exceedance alarm indicators so that managers could choose to develop demand control strategies or renegotiate the demand contract with the energy distributor.

Thus, we noticed that a tool for predictive analysis of energy demand could contribute to anticipate potential exceedances and, if possible, act promptly to reduce costs associated with consumer demand exceeding limits, also assisting in demand management. Therefore, considering that each circuit in the legacy installation can be monitored through retrofit modules, the forecasting of demand for the next 15 min of the installation and its circuits could be performed at the supervision and control center (SCC), becoming an additional data analytics functionality incorporated into audit processes to enhance energy efficiency. Such a strategy would enable decision making for demand control or renegotiation of demand limits with the utility company, if necessary.

In this study, after installing the ACU-MAIN and ACU-BREAKERs in the main power distribution panel, we let the devices operate and collect individual data from each circuit, including the main breaker. The data were collected based on the interoperability definitions specified earlier in Section 5.3. The collected circuit parameters are detailed in Table 5. Subsequently, Table 6 presents the identification and load connected to each circuit, along with the monitoring system device that supervises the respective circuits.

Table 5. Data variable description.

Data Variable	Description
Circuit identification	Monitored circuit identification.
MAC address	MAC address of installed ACU.
Timestamp	Timestamp of samples (datetime format).
Power factor	Power Factor of each circuit (%).
Active energy	Active energy of each circuit (Wh).
RMS current	RMS current of each circuit (A).
RMS voltage	RMS voltage of each circuit (V).

Table 6. Circuit, load, and monitoring device description.

Circuit Identification	Load	Monitoring Device
Circuit 0	All Building Installation	ACU-MAIN
Circuit 2	Production Line—02	ACU-BREAKER-1
Circuit 3	Production Line—03	ACU-BREAKER-2
Circuit 4	Production Line—04	ACU-BREAKER-3
Circuit 5	Reserve Circuit	ACU-BREAKER-4
Circuit 6	Electrical Panel—Production	ACU-BREAKER-5
Circuit 7	Reserve Circuit	ACU-BREAKER-6
Circuit 8	Electrical Panel—Server 02	ACU-BREAKER-7
Circuit 9	Support Area—02	ACU-BREAKER-8
Circuit 10	Central Air Conditioning—01	ACU-BREAKER-9
Circuit 11	Support Area—03	ACU-BREAKER-10
Circuit 12	Administration	ACU-BREAKER-11
Circuit 13	Central Air Conditioning—02	ACU-BREAKER-12
Circuit 14	Electrical Panel—Stock 01	ACU-BREAKER-13
Circuit 15	Support Area—01	ACU-BREAKER-14
Circuit 16	Central Air Conditioning—03	ACU-BREAKER-15
Circuit 17	Electrical Panel—Stock 02	ACU-BREAKER-16
Circuit 18	Support Area—04	ACU-BREAKER-17
Circuit 19	Electrical Panel—Server 01	ACU-BREAKER-18
Circuit 20	Reserve Circuit	ACU-BREAKER-19
Circuit 21	Chamber	ACU-BREAKER-20
Circuit 22	Reserve Circuit	ACU-BREAKER-21

The proposed system transmits the collected data from minute to minute to the local server and then to the cloud. Based on this, it was possible to create a database at the SCC for conducting the study proposed in this work. The database used in this study was generated from 15 January to 12 April 2023, and contains data from the main breaker and 21 circuits of the distribution panel that supply loads and other distribution panels within the building installation. Due to industrial confidentiality reasons, the obtained database and other company data could not be published or made available to the public at the moment, but we can make it available upon request and negotiations carried out directly with us. For the forecasting task proposed, only the minute-to-minute active energy data from each circuit will be used, which were subsequently processed to obtain the energy demand. The other data are used by the industry in energy audit procedures. It is important to mention that the building in question has a demand limit of 120 kW.

Throughout this section, we presented the exploratory analysis of the obtained data, the preprocessing techniques used for training the learning models, and the performance metrics for model evaluation. Hereafter, the concepts of the learning models used will be presented, followed by the division of the training and validation datasets.

In summary, to prepare the data for use in time series forecasting, we used the sliding window technique so that previous demand data could be used to predict future demand for the next 15 min for circuits within the installation, following the ANEEL guidelines in [57]. These data were normalized using the min–max method. Based on the performance of other works in the literature, we used machine learning regression techniques as learning models, such as random forest regressor (RFR), support vector regression (SVR), and XGBoost regressor (XGBR). Additionally, we used the linear regression (LR) method to obtain a prediction baseline from the preprocessed data, and a recurrent neural network model, specifically a long short-term memory (LSTM) network, as a deep learning alternative to compare with the other obtained results.

6.1. Exploratory Data Analysis and Definition of the Circuits to Be Analyzed

Before preprocessing the obtained data, we analyzed the contribution of each circuit to the energy consumption of the building installation. For this purpose, we performed a Pareto analysis of the total energy consumption of the circuits in the installation from 15 January to 12 April 2023. In this analysis, the cumulative percentage consumption was based on the ratio of the individual consumption of each circuit, monitored by the ACU operators, to the total consumption of the installation measured by the ACU-BREAKER. Circuit 0 represents the entire installation, which is monitored by the ACU-MAIN. The other circuits, from 2 to 22, are monitored through the ACU-BREAKERs. The Pareto diagram of the energy consumption of the circuits present in the installation is illustrated in Figure 8. It should be noted that, due to damage to the ACU-BREAKER of circuit 1 during the installation process and the fact that other circuits have much lower energy consumption compared to the rest, the total and percentage consumption of these circuits are identified as “other circuits” in the diagram.

We noticed that circuits 13, 16, 10, 8, 6, 12, and 14 accounted for approximately 80% of the total consumption of the installation. Since energy consumption is directly related to energy demand, we chose to perform demand forecasting studies for these circuits considering their contributions to the demand increase. In addition to these circuits, we also used the demand data obtained from the ACU-MAIN. From the energy data monitored every minute by the circuits, we extracted the 15-min energy demand for the mentioned circuits. Table 7 presents the statistical and descriptive data for 15-min demand intervals for the specified circuits. Here, ”count” represents the number of demand values for each circuit’s dataset. Figure 9 illustrates box plots that detail the variation in the 15-min energy demand for these circuits.

We observed from Table 7 and Figure 9 that the average values of the 15-min demand are directly proportional to the cumulative percent of energy in Figure 8, justifying the selection of circuits based on Pareto analysis for the demand forecasting study. According to Table 7, the data count is the same for all samples collected from the selected circuits. From Table 7 and Figure 9, with the exception of circuits 6 and 8, we noticed that the largest deviations obtained are concentrated in the upper part of the graphs. We can observe from Table 7 that the standard deviation of the energy demand is more significant in the demand obtained from the monitored data of the main breaker of the distribution panel (circuit 0). Additionally, it can be observed in Figure 9 that the graph indicates possible demand exceedances in the installation during the data collection period in this circuit, with values exceeding the contracted demand of 120 kW, as illustrated by the red marking in the figure. On the other hand, the outliers in the same figure are less frequent in the circuits of the main panel monitored by the ACU-BREAKERs. The circuits that present the most outliers are the demand data of circuits 8 and 12. We expect that the LSTM, SVR, RFR, and XGBR models perform better than the linear regression model in datasets with higher variability. The preprocessing techniques applied to the 15-min demand data, which are subsequently used in the training and testing of the learning models, will be presented next.

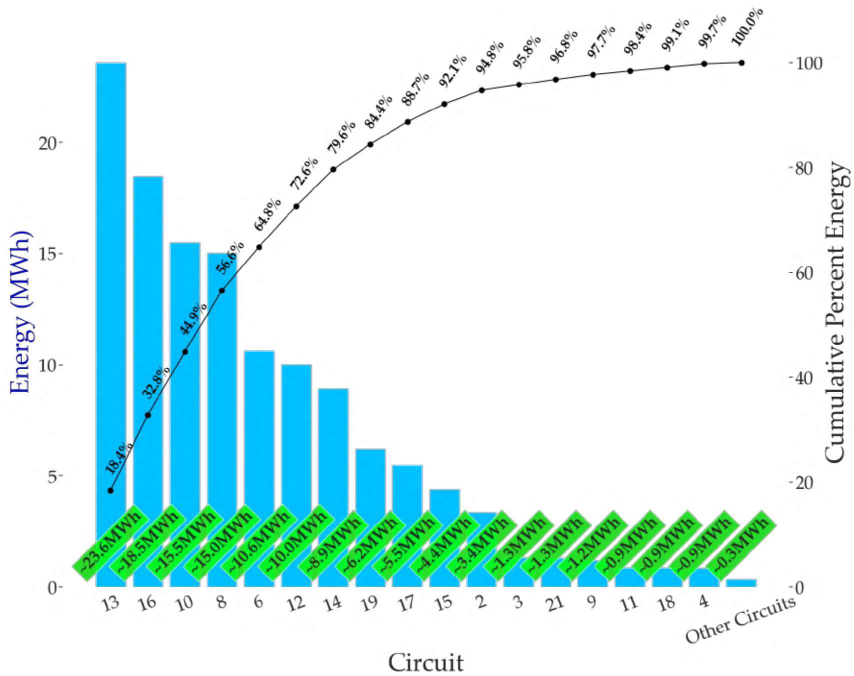

Figure 8. Pareto diagram of the energy consumption of building circuits.

Table 7. Descriptive statistics of the 15-min demand data.

Statistics	Circ. 0	Circ. 6	Circ. 8	Circ. 10	Circ. 12	Circ. 13	Circ. 14	Circ. 16
Count	6782	6782	6782	6782	6782	6782	6782	6782
Mean (kW)	62.18	6.27	8.86	9.13	5.90	13.92	5.27	10.90
Standard deviation (kW)	34.18	3.55	3.22	8.90	4.92	11.24	3.33	9.67
Lower value (kW)	9.25	0.54	0.09	0.11	0.66	0.46	0.45	0.11
First quartile (kW)	21.74	1.45	9.02	0.12	1.52	0.57	0.87	0.12
Median (kW)	72.35	8.57	9.79	5.49	3.76	20.14	6.51	11.11
Third quartile (kW)	89.60	8.79	10.44	19.52	9.80	24.33	8.13	22.30
Upper value (kW)	126.46	10.80	13.46	21.59	25.07	27.44	11.74	24.14

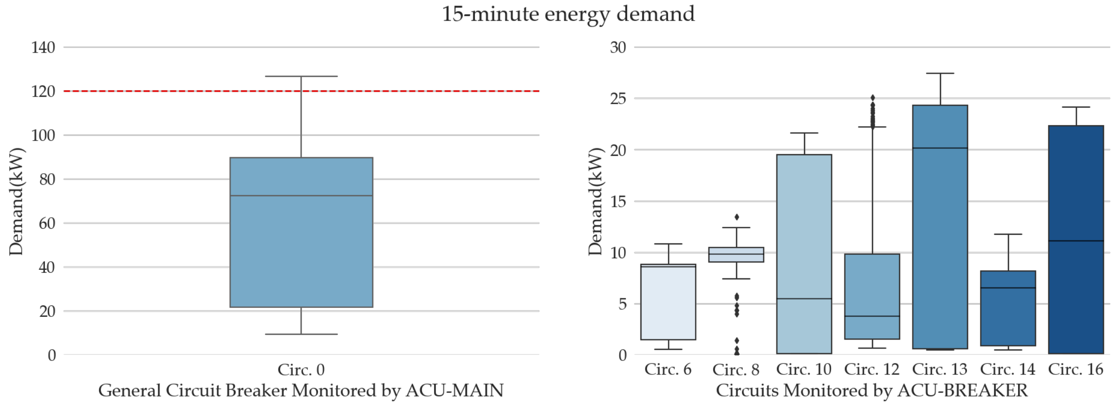

Figure 9. 15-min demand variation of the building installation and monitored circuits, with the contracted demand of the installation represented by a dashed red line.

6.2. Data Preprocessing

In this section, we present the methods used for data preprocessing in our study, which include the sliding window technique and min–max normalization. This crucial step ensures that the data entered into the models are in a suitable and ideal format for forecasting energy demand in the context of this work.

6.2.1. Sliding Window

The sliding window algorithm was used to generate the input data for the models by selecting subsets of sequential samples. These subsets are called sliding windows, which move with a predetermined temporal unit step according to each application [58]. This technique is widely used in areas such as time series forecasting, signal processing, and temporal data analysis. In this work, the temporal unit is defined as the energy demand values obtained from each circuit over a 15-min period. Each sliding window, as illustrated in Figure 10, is composed of past demand values (i.e., blue sets), which are used as input to predict the energy demand for the next temporal unit (i.e., cubes). We determined the optimal window size through empirical tests, where we established possible window values and performed iterative loops using the learning models. Based on the results obtained for each defined window, we have selected the best possible window size to predict the demand for the selected circuits. The window size determined from the conducted tests was 10 temporal units (samples) of 15 min of previous demands to predict the value of the energy demand for the subsequent sample.

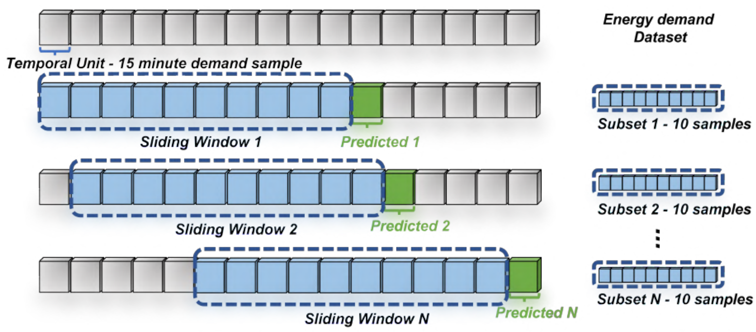

Figure 10. Sliding window technique.

6.2.2. Min–Max Normalization

The min–max data normalization method scales a dataset so that its values are within a specified range $[\mathbf{a}, \mathbf{b}]$. This technique is commonly used to preprocess data before applying machine learning algorithms. When applying min–max normalization to a dataset, the original values are transformed into new scaled values that fall within a specified range. This transformation is performed using an adaptation of the standard linear transformation, as shown in Equation (1). In this work, the range defined for data normalization was $[\mathbf{0}, \mathbf{1}]$.

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

6.3. Evaluation Metrics

In this section, we explain the critical metrics used to evaluate the performance of the implemented learning models. These evaluation metrics provide quantitative information about the performance of the models in forecasting energy demand.

6.3.1. Root Mean Squared Error—RMSE

Root mean squared error (RMSE) is a widely used metric for evaluating the performance of regression models. This measure assesses the difference between the actual values y_i and the predicted values $\hat{y}_i$ of a dependent variable by calculating the square root of the mean of the squared errors, as shown in Equation (2).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)} \tag{2}$$

By examining the equation of RMSE, it can be seen that the metric resembles the standard deviation. Thus, the RMSE value can be interpreted as a metric that indicates the variability in errors in relation to the actual values of the dependent variable. Therefore, it can be considered as an indicator of the model's accuracy, with a lower RMSE value indicating better performance. Additionally, the RMSE metric can be used as a quantitative measure of the prediction quality of the model for comparative analysis between regression techniques. It is worth noting the use of the square root, the RMSE can be interpreted in terms of the dependent variable, which helps in understanding the magnitude of errors generated by the evaluated model [59].

6.3.2. Mean Absolute Error—MAE

Mean absolute error (MAE) is an evaluation metric that provides the average magnitude of the n absolute differences between the predicted values y_i and the expected values $\hat{y}_i$. This metric is expressed in the same unit as the dependent variable and, therefore, provides a straightforward understanding and interpretation of the achieved performance, facilitating a direct comparison between different models [60]. The mathematical expression for MAE can be seen in Equation (3).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{3}$$

6.3.3. R-Squared Score—R²

The R-squared score (R^2) is an evaluation metric that indicates the proportion of the variance in the dependent/predicted variable y that is explained by the input/expected variables. This metric takes values between 0 and 1, where 0 indicates that the model does not explain any variability in the dependent variable, and 1 indicates that the model explains all the variability in the dependent variable. Therefore, as the R^2 value increases, the model fits the data better and explains a higher proportion of the variance in the dependent variable. On the other hand, an R^2 value close to 0 indicates that the model is unable to explain the variation in the dependent variable [61]. This metric is expressed in Equation (4).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{4}$$

6.4. Learning Models

In this section, we delve into the specificities of the learning models used in this work, which include linear regression, support vector regression, random forest regression (RFR), XGBoost regression, and LSTM-type recurrent networks.

6.4.1. Linear Regression (LR)

The linear regression (LR) method aims to establish a linear relationship between the response variable y and the predictor variables $x_1, x_2, \ldots, x_l$, which are called the dependent and independent variables, respectively. In the context of demand prediction, the independent variable is the sampled data allocated in the window, while the dependent variable is the predicted demand. The linear relationship is obtained by estimating the parameter vector θ and adding an additive disturbance or noise term η. Thus, considering y_n as the demand at time n, and applying the sliding window, it follows that:

$$y_n = \theta_0 + \theta_1 y_{n-1} + \theta_2 y_{n-2} + \ldots + \theta_l y_{n-l} + \eta_n \tag{5}$$

and

$$\eta_n = y_n - (\theta_0 + \theta_1 y_{n-1} + \theta_2 y_{n-2} + \ldots + \theta_l y_{n-l}) \tag{6}$$

Considering N observations and $l = 10$, we have:

$$S(\theta) = \sum_{n=l+1}^{N} (y_n - \theta_1 y_{n-1} - \theta_2 y_{n-2} - \ldots - \theta_l y_{n-l})^2 \tag{7}$$

$$S(\theta) = \sum_{n=l+1}^{N} \eta_n^2 \tag{8}$$

or in vector form:

$$S(\theta) = \sum_{n=l+1}^{N} (y_n - \theta^T \tilde{y}_n)^2 \tag{9}$$

where

$$\theta = (\theta_0, \theta_1, \ldots, \theta_l)^T \tag{10}$$

and

$$\tilde{y}_n = (1, y_{n-1}, y_{n-2}, \ldots, y_{n-l})^T \tag{11}$$

In this case, $w = (w_0, w_1, \ldots, w_l)^T$ is the estimated vector of θ that minimizes $S(\theta)$. In general terms, the LR model performs a prediction by calculating the weighted sum of the input data and adding a constant term. This process determines the weights and biases of the model. In its multiple form, it involves the use of two or more predictors, i.e., more input variables for training. It is one of the most commonly used low-complexity models when the response variable and predictor have a strong linear correlation [62].

6.4.2. Support Vector Regression (SVR)

The SVR (support vector regression) prediction technique aims to predict output values by determining a hyperplane that closely resembles the input data. In this algorithm, the maximum number of instances possible is considered within a margin of ϵ, with the aim of determining weights and biases, that provides the generalization for the model. To achieve this, the objective is to minimize the error $J(w, w_0, \xi, \hat{\xi})$ given by Equation (12), where ξ_n and $\hat{\xi_n}$ are the slack variables corresponding to a deviation from the ϵ margin, with the penalty control given by C, constrained by Equations (13)–(15).

$$J(w, w_0, \xi, \hat{\xi}) = \frac{1}{2}||w||^2 + C\left(\sum_{n=1}^{N} \xi_n + \sum_{n=1}^{N} \hat{\xi_n}\right) \tag{12}$$

$$y_n - w^T x_n - w_0 \leq \epsilon + \hat{\xi_n},\ n = 1, 2, \ldots, N \tag{13}$$

$$w^T x_n + w_0 - y_n \leq \epsilon + \xi_n,\ n = 1, 2, \ldots, N \tag{14}$$

$$\hat{\xi_n} \geq 0, \xi_n \geq 0,\ n = 1, 2, \ldots, N \tag{15}$$

In this way, contributions to the cost function from errors with an absolute value less than or equal to ξ are set to zero. The optimizer's objective is to estimate w and w_0 in a manner that the contribution of error values greater than ξ and smaller than $\hat{\xi}$ is minimized. Thus, this algorithm is interesting for initial testing in machine learning and has the advantage of not being affected by local minima, unlike deep neural network algorithms. However, as the amount of data increases, this algorithm tends to lose performance when attempting to establish a linear response [63].

6.4.3. Random Forest Regression (RFR)

In a regression tree, the determination of the root node variable and subsequent nodes is defined by maximizing the weighted averages in the child nodes or, equivalently, by minimizing the weighted variance σ_w^2 of subsets $Y_1,\ Y_2, \ldots, Y_n$, with $|Y_1|,\ |Y_2|, \ldots, |Y_n|$ elements, as shown in Equation (16).

$$\sigma_w^2(Y_1, Y_2, \ldots, Y_n) = \sum_{n=1}^{N} \frac{|Y_n|}{|Y|} \sigma^2(Y_n) \tag{16}$$

In the RF method, which is an algorithm based on an ensemble of decision trees, the bootstrap aggregating strategy is applied during the model learning phase. Bootstrap aggregating aims to construct a series of trees by randomly sampling the original data, using only a subset m of predictors from a complete set p of predictors. These samples are then trained independently and in parallel with each other. Finally, the values are aggregated by calculating the average of the results obtained from each individual regression tree [64].

Thus, by averaging multiple decision trees that are subjected to high variance, the model exhibits better generalization performance and is less prone to overfitting. The RF technique has been widely used to solve low-complexity regression problems due to its high performance and robustness against overfitting.

6.4.4. XGBoost Regressor (XGBR)

The XGBoost regressor algorithm is based on making predictions using regression decision trees. The method utilizes information aggregation, random forest for tree selection during batch training, error minimization using gradient descent, and regularization of weights and biases. Equations (17) and (18) present the weight function and the objective function, respectively. In these equations, g_i and h_i are the first- and second-order gradients of the loss function, λ and γ represent additional regularization terms, T represents the number of nodes, q represents the tree structure, and I_j is the instances of a node j. In addition to regularization, XGBoost uses an additional shrinkage technique to prevent overfitting by scaling the weights obtained by a factor η, similar to a learning rate. This process reduces the influence of each individual tree and allows room for future trees to improve the model.

$$w_j = -\frac{\sum_{i \in I_j} g_i}{\sum_{i \in I_j} h_i + \lambda} \tag{17}$$

$$J(q) = -\frac{1}{2} \sum_{j=1}^{T} \frac{(\sum_{i \in I_j} g_i)^2}{\sum_{i \in I_j} h_i + \lambda} + \gamma T \tag{18}$$

This algorithm has shown promise in various prediction scenarios, including regression and classification problems. This is due to its high scalability, as the execution time of this algorithm can be 10 times faster than others, and it can be scaled for numerous examples in distributed configurations or with limited processing memory due to implemented optimizations and parallel processing capabilities [65].

6.4.5. Long Short-Term Memory (LSTM)

LSTM networks are a type of recurrent neural network that feature an internal memory cell structure as their main characteristic. Through the logistic function and multiplier weight matrices, these gates are implemented and referred to as the input gate (i_t), forget gate (f_t), and output gate (o_t). There is also the vector that represents the internal state (C_t) of the LSTM cell and the candidate value ($\tilde{C}_t$). The mathematical definitions of the gates, cell state, and candidate value of the LSTM network are presented in Equations (19)–(23), including the respective biases b_C, b_i, b_f, and b_o.

$$f_t = \sigma(W_f[h_{t-1}, x_t\,] + b_f) \tag{19}$$

$$i_t = \sigma(W_i[h_{t-1}, x_t\,] + b_i) \tag{20}$$

$$o_t = \sigma(W_o[h_{t-1}, x_t\,] + b_o) \tag{21}$$

$$C_t = f_t \circ C_{t-1} + i_t \circ \tilde{C}_t \tag{22}$$

$$\tilde{C}_t \cong \tanh(W_c[h_{t-1}, x_t\,] + b_C) \tag{23}$$

The application of these networks is interesting for problems involving sequential data and time series, such as the electrical demand curve, for example, [66]. While a fully connected neural network has separate parameters for each input feature, recurrent neural networks share the same weights across different time steps, establishing a strong temporal relationship among the data.

6.5. Definition of Training and Test Sets

The demand data for the selected circuits consists of 6782 observations, as shown in Table 7. To proceed, we normalized the dataset using the min–max technique, we divided it into training and test subsets in order to implement and validate the learning models. Thus, 80% of the observations were used for training, and 20% were used for testing. Figure 11 illustrates the separated training and test sets for each circuit selected for the proposed demand prediction study in this work. After dividing the data, we applied the sliding window technique to prepare the input and output data subsets for training and testing the learning models. As mentioned earlier, the sliding window size adopted was 10 past values to predict a demand value for the next 15 min.

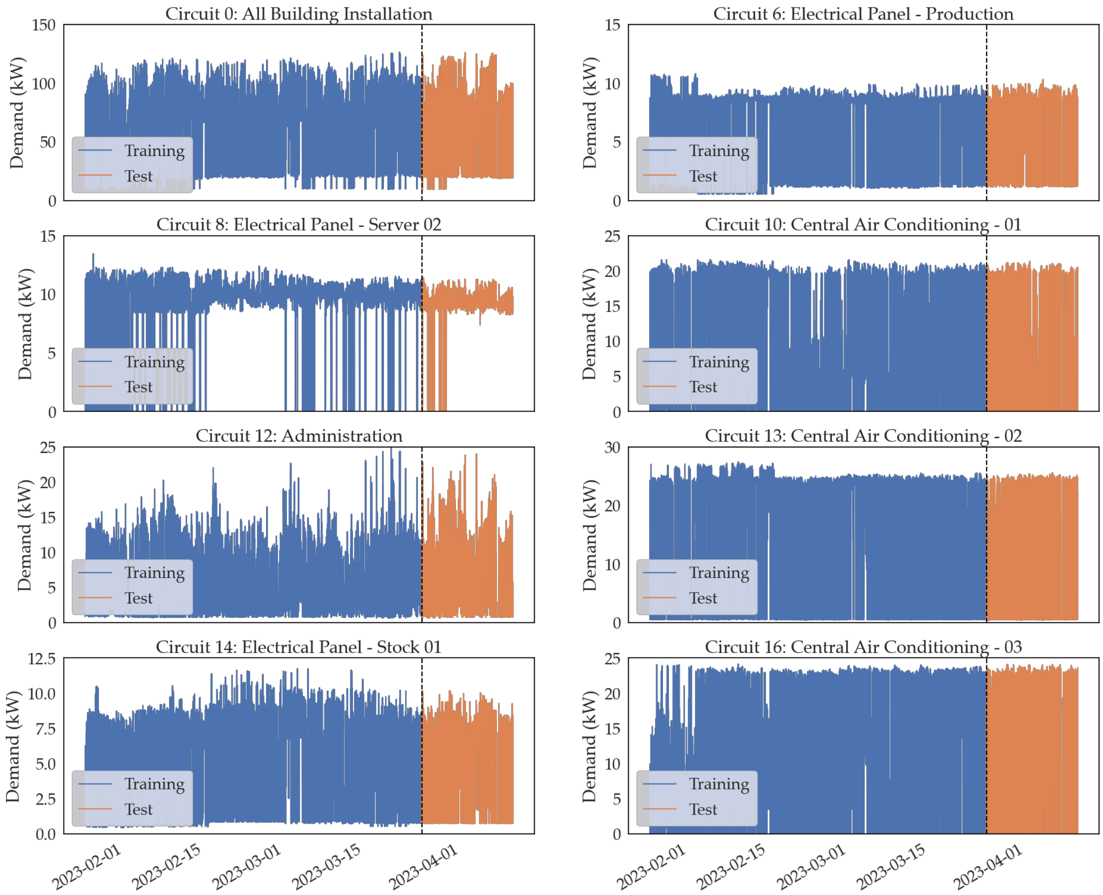

Figure 11. Training and test sets of the selected circuits.

The training of the models was carried out on a local server from the data collected in the SCC, where we evaluated the predictive models before transferring them back to the cloud server. The server has a 2.3 GHz Intel Core i7-11800H processor, 16 GB RAM, 4 GB GPU, and 500 GB SSD.

6.6. *Software Libraries and Optimization of Learning Models*

The experiments with the learning models were conducted on the Jupyter Lab platform of the Anaconda distribution using the Python language. We utilized several libraries, including TensorFlow, Pandas, NumPy, Matplotlib, Seaborn, XGBoost, and Scikit-learn. To enhance the performance of the learning models on the established dataset, we used the Optuna framework for Bayesian optimization of the hyperparameters of the machine learning models and fine-tuning of the LSTM model. Bayesian optimization techniques have proven to be more efficient in finding better hyperparameters and searching for the best parameters to be used in neural networks and their variants. This is because they make use of prior information about the behavior of the objective function to guide the search [67,68]. Optuna is an easy-to-configure Bayesian optimization framework that is suitable for hyperparameter tuning and determining the best parameters for supervised learning models for a given training and testing set. With a define-by-run API, the search space for the best parameters is dynamically defined by Optuna during the runtime of an objective function instantiated to test the desired model under pre-established conditions [69]. Thus, Optuna was used to train and evaluate the models for each dataset of the selected circuits. The parameter K in the table represents the number of trees used in the RFR and XGBR models.

6.7. Definition of Parameters and Architectures of Learning Models

To accomplish the task of energy demand forecasting in our proposal, we conducted an investigation into various machine learning models to determine the most suitable one(s) for predicting the energy demand of the researched circuits, which exhibit distinct demand patterns. The architecture for evaluating the learning models is illustrated in Figure 12a, and the implemented LSTM model architecture is represented in Figure 12b. After conducting tests using the Optuna framework to evaluate the models, we were able to select the best parameters for each learning model. The tests were conducted individually for each model, considering the normalized datasets of circuits 0, 6, 8, 10, 12, 13, 14, and 16. We conducted 500 trials per study in an effort to find the optimal parameters that enabled the models to effectively capture the temporal demand characteristics. The mean squared error (MSE) metric was used as the evaluation criterion for training all the machine learning models. Table 8 showcases some of the hyperparameters discovered for the machine learning models after the Bayesian optimization process, considering the selected datasets.

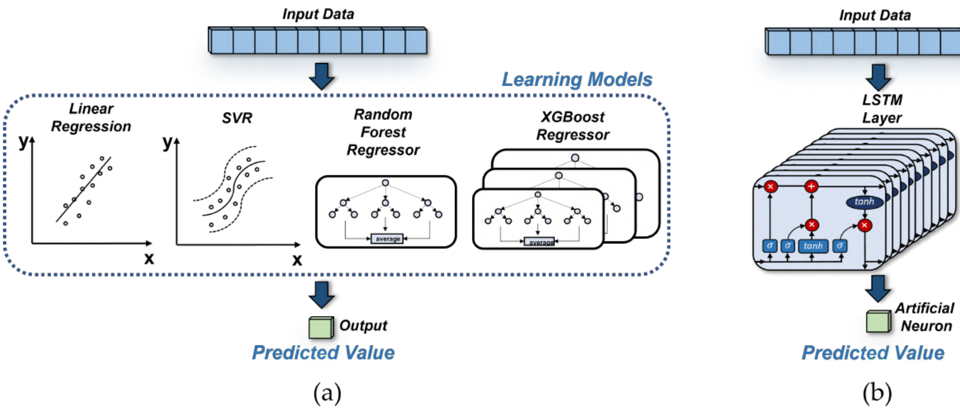

Figure 12. Learning models (**a**) and LSTM recurrent neural network model (**b**) used to evaluate demand forecasting.

Table 8. Hyperparameters used in machine learning models after optimization process.

Dataset	SVR	RFR	XGBR
Circ. 0	C: 115.495, ϵ: 0.011	K: 236	γ: 0.107, λ: 0.036, η: 0.207, K: 645
Circ. 6	C: 119.050, ϵ: 0.034	K: 558	γ: 0.273, λ: 0.898, η: 0.308, K: 530
Circ. 8	C: 53.516, ϵ: 0.011	K: 102	γ: 0.072, λ: 0.538, η: 0.242, K: 684
Circ. 10	C: 108.645, ϵ: 0.028	K: 498	γ: 0.407, λ: 0.238, η: 0.245, K: 505
Circ. 12	C: 51.044, ϵ: 0.014	K: 132	γ: 0.059, λ: 0.859, η: 0.260, K: 500
Circ. 13	C: 119.953, ϵ: 0.031	K: 217	γ: 0.254, λ: 0.284, η: 0.034, K: 555
Circ. 14	C: 108.214, ϵ: 0.018	K: 43	γ: 0.205, λ: 0.914, η: 0.246, K: 549
Circ. 16	C: 117.43, ϵ: 0.055	K: 408	γ: 0.255, λ: 0.458, η: 0.173, K: 569

K: number of trees.

When implementing the SVR, RFR, and XGBR models, it is crucial to understand the impact of the chosen parameters following the optimization process. In the case of SVR, the parameters C and ϵ control the regularization and error tolerance, respectively. Higher values of C can lead to overfitting, while very low values can result in underfitting. The parameter ϵ determines the width of the tolerance margin around the regression hyperplane. Therefore, the optimization process using the Optuna framework was crucial in selecting appropriate parameters and improving the SVR's performance. On the other hand, in the RFR model, the number of estimators (trees) K, determined through the optimization process, improves the model's generalization capability and reduces both the training and optimization times. The XGBR model also has several important parameters, such as the learning rate (η) and the number of estimators (K). The learning rate controls the contribution of each estimator in the update process. Lower values can lead to better generalization, while higher values can cause overfitting. The number of estimators affects the model's generalization capability and training time.

We also implemented an LSTM neural network model to compare with the LR, SVR, RFR, and XGBR models. In the implementation process of this model, we tested various architectures, including bidirectional LSTM networks and hybrid LSTM and convolutional networks. We also experimented with stacking LSTM layers to achieve better results. However, the best performance for the test set was obtained using a single LSTM layer with one artificial neuron in the output. We also utilized Optuna to optimize the parameters of the proposed LSTM network. Each Optuna trial for the LSTM network consisted of 100 training epochs using the Adam optimizer [66]. We conducted 500 trials for this model in the Optuna framework. The best parameters for this model are presented in Table 9. It is important to note that the activation function used in the LSTM layer of the models was the hyperbolic tangent (tanh).

Table 9. Best parameters for LSTM model on each dataset.

Dataset	Learning Rate	Units	Batch Size
Circ. 0	3.209×10^{-2}	38	70
Circ. 6	1.055×10^{-2}	23	24
Circ. 8	3.085×10^{-2}	20	23
Circ. 10	2.711×10^{-2}	80	24
Circ. 12	2.521×10^{-2}	80	70
Circ. 13	3.351×10^{-2}	48	64
Circ. 14	2.101×10^{-2}	28	36
Circ. 16	2.722×10^{-2}	80	64

The learning rate determines the step size used by the Adam optimization algorithm during the training of the LSTM. Low learning rates can result in slower convergence or become trapped in local minima, while high learning rates can make the training unstable and prevent the model from finding an optimal solution. The number of units determines the model's capacity to learn complex representations and capture patterns in the data. Higher values increase the learning capacity but also increase the training time and the need for more training data. The batch size determines the number of training samples used in each weight update pass of the LSTM. A larger batch size can speed up training by processing more samples in parallel. However, a larger batch size requires more memory, and training may become more challenging to parallelize. The choice of batch size depends on the available memory, the size of the training set, and the trade-off between training speed and accuracy. Thus, finding the appropriate parameters is crucial for striking a balance between training speed and the performance of the LSTM model.

7. Results

7.1. Performance Evaluation of Learning Models

Initially, we assessed the LR model's performance on the acquired datasets to establish a baseline for the performance metrics, to be achieved by the other learning models. After optimizing the learning models, we used the hyperparameters from Table 8 to evaluate the performance of the SVR, RFR, and XGBR models, and the parameters from Table 9 to evaluate the performance of the LSTM model. The performance metrics obtained for the learning models for the test subsets of each energy demand dataset are presented in Table 10. It is important to mention that the results presented for the performance metrics are not normalized, as the data were returned to their original scale after the models' predictions.

Table 10. Result of learning models' performance metrics for test sets of selected demands (non-normalized values).

Demand	RMSE (kW)					MAE (kW)					R^2 (%)				
Dataset	LR	SVR	RFR	XGBR	LSTM	LR	SVR	RFR	XGBR	LSTM	LR	SVR	RFR	XGBR	LSTM
Circ. 0	9.116	8.789	8.269	8.252	**8.216** *	4.874	4.278	**4.152** *	4.273	4.285	92.705	93.22	93.998	94.02	**94.07** *
Circ. 6	0.957	0.936	0.875	0.868	**0.865** *	0.312	0.321	0.267	0.272	**0.251** *	91.94	92.29	93.26	93.37	**93.52** *
Circ. 8	0.426	0.417	0.424	0.420	**0.415** *	0.215	**0.199** *	0.217	0.214	0.205	86.81	87.35	86.90	87.16	**87.39** *
Circ. 10	2.987	2.948	2.753	**2.701** *	2.723	1.278	1.298	1.140	**1.120** *	1.171	89.07	89.35	90.71	**91.06** *	90.93
Circ. 12	1.296	1.291	1.302	1.317	**1.288** *	0.729	0.728	0.729	0.754	**0.694** *	94.23	94.27	94.17	94.04	**94.30** *
Circ. 13	3.192	3.116	3.007	3.021	**3.003** *	1.353	1.437	1.241	1.313	**1.238** *	91.14	91.55	92.13	92.06	**92.15** *
Circ. 14	0.670	0.656	0.595	0.606	**0.577** *	0.269	0.275	0.254	0.274	**0.243** *	95.23	95.43	96.23	96.10	**96.47** *
Circ. 16	4.825	4.461	4.011	**3.875** *	3.978	2.912	2.240	2.161	2.154	**2.202** *	75.82	79.33	83.29	**84.40** *	83.56

Values in bold with an asterisk represent the best results.

Comparatively, based on the results presented in Table 10, the LSTM recurrent neural network model demonstrated superior performance compared to the other models for the majority of the datasets. The LSTM showed good R^2 values, indicating that it can better estimate the variability in demand patterns compared to the other models. Thus, we assert that the ability of recurrent neural networks to handle temporal and sequential dependencies was beneficial for the task of demand forecasting in the selected circuit datasets. We emphasize that the optimization process conducted to select the best parameters for this model, which are presented in Table 9, was crucial for the achieved performance. On the other hand, the LR model performed the worst among the learning models. This can be attributed to the simplicity of the linear model, which, in most cases, failed to capture complex relationships in the demand data of the selected circuits. In all cases, the RMSE performance followed the results of the R^2 metric. However, the MAE metric did not always correlate with RMSE and R^2, as other models generated better results than the LSTM in this evaluation metric.

Regarding the performance of the SVR, RFR, and XGBR models, we can observe in Table 10 that they outperformed the baseline metrics of the LR model. Only in one case, the dataset of circuit 12, did the LR model perform better than the RFR and XGBR models in terms of RMSE, MAE, and R^2. Depending on the dataset and the selected parameters, at least one of the machine learning models outperformed the others. For circuits 8 and 12, the SVR model stood out among the three models. In circuits 13 and 14, the RFR model performed better than the other two models. For circuits 0, 6, 10, and 16, the XGBR, being more complex than SVR and RFR, achieved better performance. For the datasets of circuits 10 and 16, the XGBR outperformed the LSTM model, which performed better than all the other models for the other datasets. In general, we can observe that the RFR and XGBR models tend to have better performance when compared to SVR in terms of RMSE and MAE in most cases, with XGBR standing out.

Considering the descriptive statistical data presented in Table 7 and Figure 9, we can observe that the variability in average values, standard deviation, and data range of demand influences the performance of the models. In the datasets of circuits 12 and 13, for example, where there is a greater variation in the data range, the SVR and RFR models outperformed others due to their better handling of data dispersions in these datasets. For the circuit 8 data, where abnormalities (outliers) are illustrated in Figure 9, it was observed, through the R^2 metric in Table 10, that the learning models' generalization ability was significantly affected for this dataset. Additionally, in the circuit 0 dataset, which exhibits greater variations as it represents the entire installation's energy demand, we observed the highest error values. This observation also justifies the performance of the LR models, which are sensitive to outliers, variance, and complex relationships within the datasets. In such cases, more complex and flexible models, such as LSTM, might be needed for capturing demand patterns. It is important to highlight that, to enhance the performance of the LSTM networks considering the high variance of the datasets exposed in Figure 9, we observed that the Optuna optimizer sought to increase the number of LSTM units, as presented in Table 9, so that the learning model could better capture the demand patterns.

Additionally, Table 11 presents the total optimization time for each model to search for the best parameters with the Optuna framework. Subsequently, using the optimal parameters, Table 12 illustrates the training and prediction times for each learning model.

Table 11. Total study time to optimize learning models.

Demand	Total Study Time (s)			
Dataset	**SVR**	**RFR**	**XGBR**	**LSTM**
Circ. 0	507.04	515.30	1512.57	55,554.55
Circ. 6	488.40	556.79	999.02	22,786.94
Circ. 8	505.96	563.52	1308.05	3995.51
Circ. 10	537.58	605.69	1113.27	24,081.63
Circ. 12	499.79	501.52	1231.30	20,654.27
Circ. 13	521.80	508.32	891.77	27,640.51
Circ. 14	488.50	453.44	1229.87	27,559.57
Circ. 16	555.51	562.22	1333.36	18,281.69

Table 12. Training time and prediction time of learning models.

Demand	Training Time (ms)					Prediction Time (ms)				
Dataset	**LR**	**SVR**	**RFR**	**XGBR**	**LSTM**	**LR**	**SVR**	**RFR**	**XGBR**	**LSTM**
Circ. 0	35.06	228.90	117.07	3302.61	29,469.54	3.02	3.00	1.94	2.00	281.49
Circ. 6	2.00	126.98	209.68	1740.05	63,918.14	0.99	1.00	3.99	1.99	297.31
Circ. 8	1.01	106.73	31.67	2362.45	64,716.04	1.04	2.00	0.99	1.99	280.51
Circ. 10	2.10	218.34	245.26	1524.37	52,318.09	1.06	2.01	4.84	1.99	668.13
Circ. 12	0.99	61.58	53.69	1804.42	67,387.26	1.14	2.98	2.01	1.00	293.59
Circ. 13	1.99	193.57	105.97	965.42	23.293,50	1.01	3.00	1.05	1.00	269.96
Circ. 14	1.94	184.85	22.01	1186.26	44,027.02	0.99	1.00	0.99	1.51	272.30
Circ. 16	0.99	301.30	192.10	2015.23	24,600.22	1.01	2.01	5.01	2.00	295.66

Despite delivering the highest performance, the LSTM recurrent network model demanded a greater computational time for optimization, training, and prediction processes. As outlined previously in Section 6.7, the variables such as units, batch size, and learning rate significantly influenced the training duration of the LSTM models. On the other hand, the LR model demonstrated a shorter training and prediction timeframe. It is worth noting that the optimization, training, and prediction durations directly correlate with the parameters employed in the model implementation, which varied throughout the hyperparameter tuning process and the learning models' evaluation. For instance, the training time for the RFR model increased for datasets where the tree count was higher, similar to the XGBR model when comparing the results in Table 12 with the hyperparameters displayed in Table 8. In the case of SVR, the regularization parameter C directly impacted the training duration. The XGBR model occupied the second-longest computational time in the training process, while the SVR and RFR models alternated between the measured durations during the analysis. Hence, for demand data where the training parameters demanded a larger computational effort, the models' training time was extended, subsequently influencing the optimization time for the selected dataset. It is crucial to underscore that, as per Section 6.4.4, although the XGBR model necessitated more training time, its prediction duration was reduced, aligning it closely with simpler models such as LR.

7.2. Evaluation of Our Proposal for Demand Forecast

Table 13 outlines the count of actual demand exceedances beyond 120 kW sourced from the building installation's test data subset (circuit 0), alongside the number of demand exceedances forecasted by each learning model throughout the period from 25 March to 12 April 2023, representing the test set of demand data.

Table 13. Actual and predicted number of demand overruns by learning models.

Actual	LR	SVR	RFR	XGBR	LSTM
38	22	24	30	30	32

As demonstrated, during the testing period for the implemented models, the LSTM model, notwithstanding its higher computational cost for training, proved more effective than other models in the forecasting task. This makes it ideal for use in the SCC to predict the energy demand for the upcoming 15-min intervals in order to avoid demand exceedances. In this context, the LR and SVR models fell short in detecting these exceedances, while the RFR and XGBR models exhibited similar performance. Consequently, the metrics and results elaborated in the prior section align with the comparison made in Table 13.

For comparison purposes, Figure 13 depicts the predictions made by the examined models from 1:00 a.m. on 7 April to 8:00 a.m. on 8 April 2023. The figure highlights the precision with which the models forecast the demand, particularly during periods of minimal variation. Generally speaking, it is observed that the LR, RFR, and SVR models tend to be less precise during moments of variation in comparison to the XGBR and LSTM models. However, during instances of high variation, such as shown for the data from circuit 16, the models are prone to consistent errors that impair their performance in achieving forecasting metrics. Additionally, Figure 14 showcases both actual and forecasted demands using the LSTM neural network models for each circuit's test sets during the period from 26 March to 4 April 2023. For the data from circuits 10, 13, and 16, we highlighted periods of high variance in energy demand in yellow, where the LSTM model did not perform adequately. This situation might be prevalent for loads with constant energy demand variation, as in the case of the three air conditioning units in the installation. Under these circumstances, the RMSE metric penalizes the performance of learning models sensitive to these variations. Consequently, a similar outcome is reflected in the R^2 metric since the model fails to accurately capture these variations. To mitigate these inaccuracies, we could contemplate incorporating other correlated data or different forecasting techniques to enhance the predictability of the forecasting models.

For the circuit 0 data, which represents the entire building installation, we marked in dashed red lines the contracted demand of 120 kW, as shown in Figure 14. From April 1, we observed that the installation's demand exceeded the contracted demand in certain periods. These demand exceedance events are marked in dark red in the figure, both for the installation data (circuit 0) and for the data from the other circuits. We also highlighted in light red the periods in which the circuits had increased demand compared to the data observed in previous periods. We noticed that the algorithm generated forecasts that closely tracked the actual values over time. We suggest using these forecasts to guide the control of the installation's demand and avoid potential exceedances.

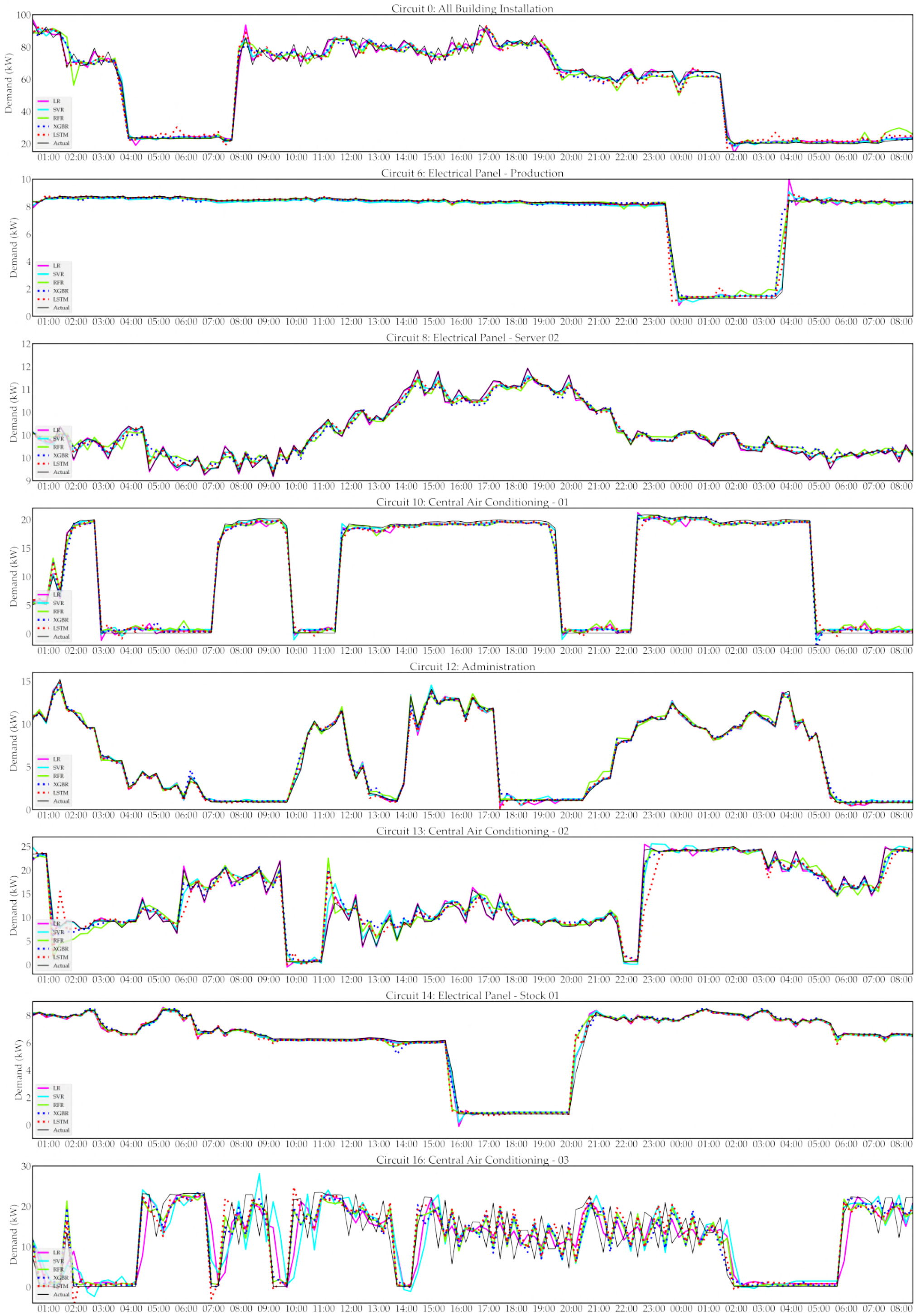

Figure 13. Actual (black) and predicted demand by the LR (magenta), SVR (cyan), RFR (green), XGBR (blue dashed), and LSTM (red dashed) models during the period 01:00 a.m. on 7 April 2023 until 08:00 a.m. of 8 April 2023.

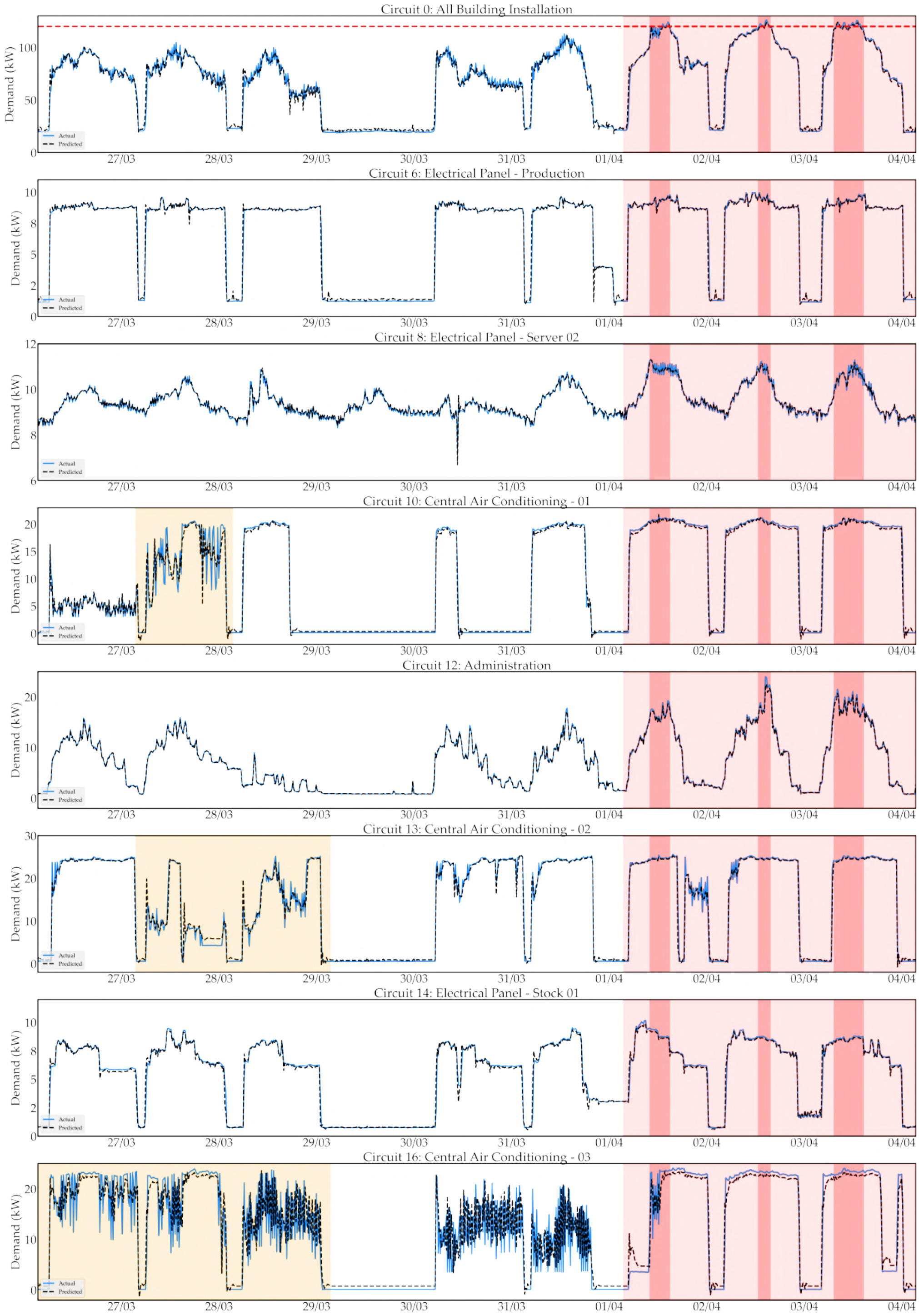

Figure 14. Contracted demand (dashed red), and actual (blue) and predicted values (dashed black) for the 15-min power demand of the selected circuits using the respective proposed LSTM recurrent network models in the period from 26 May to 4 April 2023.

7.3. Discussion of the Results Obtained from the Monitoring Proposal

We implemented a cluster of sensor devices that communicate within a power distribution panel using an ad hoc wireless network. These devices transmit electrical parameters from a building installation and its circuits to a local server, and subsequently to a supervision and control center (SCC). Our proposal's development was based on SmartLVGrid metamodel, which advocates technological updates through the retrofitting of existing systems. To implement the middleware layer of this model, we designed two energy monitoring devices: the ACU-MAIN and the ACU-BREAKER. The ACU-MAIN is responsible for monitoring the main power bus of the installation's distribution panel and acts as a concentrator for the ACU-BREAKER cluster, which monitors the energy consumption of the remaining circuits in the panel.

During the implementation of the ACU-BREAKER and ACU-MAIN devices, we took into account the physical space constraints available in the panel for installation. Therefore, we proposed a novel approach for retrofitting breakers by updating the ACU-BREAKER device compared to the work presented in [5]. This approach facilitates the physical connection interface with the monitoring device, enabling the digital convergence of legacy infrastructure to the smart buildings paradigm. Additionally, we implemented an interoperability layer using request and response message exchanges that travel through the physical layer of the IEEE 802.11 standard via the ESP-NOW protocol. This wireless communication enables our retrofitting proposal without the need for additional wired ethernet network points, following the directives of the factory in which our study took place. Thus, we enable flexible retrofitting of the installation by leveraging pre-existing resources and adding capabilities to enable energy management.

Our proposal has been operating continuously and uninterruptedly since the start of data collection after its installation, validating our approach to building energy monitoring retrofitting. As a result, we were able to build a database containing energy data from the legacy installation for its managers, including power factor, active energy, current, and voltage data for both the overall installation and individual circuits. This has enabled data-driven energy management of the legacy installation, as the monitored data became available in databases and dashboards at the supervision and control center (SCC).

7.4. Discussion of the Results Obtained for Forecasting Energy Demand in the Proposed Scenario

Based on the Brazilian regulatory resolution ANEEL n° 1000/2021 [57], the consumer unit in question falls under the binomial tariff structure. In this case, it is charged based on both consumption and a contracted limit demand, which is measured by the energy utility every 15 min. Incidentally, during periods of high production, the factory exceeds the contracted demand of 120 kW and consequently incurs penalties. With the collected database, we conducted an analysis of the loads that contribute the most to the increase in consumption and demand exceedances of the installation using Pareto analysis. We identified seven loads that contribute to nearly 80% of the total installation consumption. Based on this, we analyzed the variations in energy demand every 15 min for the loads of these circuits. To perform our analysis, we applied the sliding window technique with 10 previous demand samples and min–max normalization as a processing step for demand forecasting for the next 15 min. Subsequently, we employed various learning models, namely, linear regression (LR), support vector regressor (SVR), random forest regressor (RFR), XGBoost regressor (XGBR), and a long short-term memory (LSTM) recurrent neural network model. We evaluated the performance of each model and, to ensure the best possible performance, we utilized the optimization framework Optuna to search for the best parameters for the demand data of each selected circuit.

We observed that the LSTM model performed the best, followed by the XGBR, RFR, and SVR models, respectively. The LSTM model was able to capture the demand pattern of the selected circuits most effectively, as shown in the metrics presented in Table 10, and it predicted the highest number of demand exceedances for the test set, as shown in Table 13. However, the LSTM model required the longest computation time for optimization, training, and making predictions (Tables 11 and 12). All the other models outperformed the baseline LR metrics, with notable performance from the XGBR model, which outperformed LSTM for two datasets (circuits 10 and 16). This opens up opportunities for future neural network architectures that can surpass the metrics presented in Table 10. In Figure 14, we can observe that the predictions made by the LSTM model performed well for the selected circuit datasets. We noted that depending on the nature of the monitored loads, there may be data variations that could affect the predictability of the forecasting algorithms. We hope that by increasing the dataset size and incorporating other variables correlated with demand and seasonality, we can improve the performance of the learning algorithms for demand forecasting tasks. In our research, we have achieved the objective of demonstrating the impact and relevance of monitoring and forecasting the energy demand of circuits in a legacy building installation, aiming to detect possible breaches of contracted demand and identify the circuits where action should be taken to rectify demand transgressions in line with the regulatory framework of the Brazilian energy system.

8. Conclusions

In this work, we developed an AIoT strategy that performs energy demand forecasting for a legacy building installation and its circuits for the next 15 min, based on the retrofit of the pre-existing energy system and the premises of the SmartLVGrid metamodel. The protocols of the SmartLVGrid metamodel enabled us to design an architecture that facilitates the technological transformation of a legacy installation into the smart buildings paradigm, making the most of the existing resources.

During the development of this study, we conceived a cluster of sensor devices called ACU-BREAKERs that monitor the individual electrical parameters of each electrical circuit and communicate through an ESP-NOW ad hoc network with a coordinating device called ACU-MAIN. In our proposal, the ACU-MAIN device performs multiple functions, including coordinating data requests from other ACUs, monitoring the main power bus of the installation, and transmitting the collected data via ethernet to a locally available server within the installation. The server, in turn, forwards the collected data to the cloud-hosted SCC, where data analysis is conducted to improve the energy management processes.

Our proposal operated continuously from 15 January to 12 April 2023, and with the data obtained we conducted statistical analyses to identify the loads that contributed the most to the increase in consumption and energy demand of the installation. Based on Brazilian regulations, we focused on forecasting for the next 15 min to detect possible demand surpasses in the installation and identify the main loads causing this transgression. In this way, we provided data-driven insights for decision making regarding possible surpasses and where and when to act to control the load demand.

We employed preprocessing techniques such as sliding window for dividing the training and testing datasets of each circuit, along with min–max normalization of the data. As learning models, we used LR as the baseline for evaluating the machine learning models SVR, RFR, XGBR, and an LSTM-based recurrent neural network model. The hyperparameters of each learning model were optimized using the Optuna framework for Bayesian optimization, in order to extract the best possible performance. Subsequently, we evaluated the learning models, and the LSTM model outperformed the other learning models, followed by XGBR, RFR, SVR, and LR. In this order, the models had longer training and optimization times. We also evaluated which models successfully predicted the highest number of demand surpasses, with a highlight on the LSTM and XGBR models.

It is important to emphasize that we evaluated a model for each dataset of each circuit. For the construction of building electrical systems with more circuits and power boards, the implementation of learning models for each dataset could become unfeasible. In addition, for other cases and systems, the use of other learning models, preprocessing, and feature selection methods and other retrofit strategies could be adopted to obtain better results for the benefit of a more sustainable building ecosystem.

However, whether to optimize the use of energy inputs or to plan operations in building facilities, in our proposal, the forecast and monitoring of energy demand allow data-based management of pre-existing energy systems in legacy facilities. In precarious scenarios, without infrastructure or resources to implement modern control and communication systems, our retrofit architecture facilitates a non-abrupt digital transformation towards smart building convergence, leveraging AIoT concepts and predictive models based on wireless network data. In addition, we digitized the installation's circuits using the assumptions of our retrofit architecture, which recommends taking advantage of existing resources through well-defined protocol stacks. We emphasize that the proposed architecture represents an alternative for using electrical parameters from legacy circuits to create databases for predictive analysis, such as the energy demand forecast presented in this work. Thus, it is possible to guarantee the sustainability and improve the energy efficiency of old building installations.

9. Future Perspectives

Once we make the electrical system observable and allocate resources for demand forecasting, we enable the management of current and future energy resources from the demand side. Therefore, for future work, we suggest allocating local intelligence resources to implement new strategies that include demand control of the installation based on local business rules. This can be achieved by controlling the loads present in the installation's circuits, as we know which loads will affect the installation during demand exceedances. By also forecasting the demand of the installation's loads, we suggest utilizing distributed energy resources to inject the necessary energy to compensate for the energy demand during peak moments, avoiding possible exceedances from the energy generation side. In this way, renewable or non-renewable resources can be activated based on the proposed predictive intelligence to partially or fully meet the installation's energy demand.

Additionally, we suggest that this process may involve new dynamic energy markets, where energy sources from free energy markets can be negotiated and utilized depending on the predictability scenario of demand exceedances to reduce the costs associated with possible exceedances. The prediction task can also analyze future energy costs, recommending potential energy suppliers based on this dynamic analysis. Further work in this field can explore other prediction resources based on other energy aspects of a building installation, involving protection systems, energy consumption, or power quality. This includes studies focused on optimizing energy utilization and mitigating harmonics in the installation.

From the perspective of artificial intelligence models, we suggest evaluating the proposed strategy for other learning model architectures and datasets, including variations of the LSTM recurrent neural network model in the context of building electrical circuits in smart buildings. We also recommend using other preprocessing techniques and different sliding window sizes to assess the performance of the learning models in short, medium, and long-term prediction contexts, depending on the study's needs. For future work, we suggest exploring knowledge transfer techniques to facilitate the training of other learning models for circuits within the same cluster and for clusters located in other locations or installations. In this work, we developed specialized demand forecasting models for each circuit of the installation, which can make it costly to maintain the system in some cases. Through knowledge transfer techniques, it is possible to generalize the demand pattern capturing techniques for circuits in a building installation and scale this strategy to other cases and systems, involving the same installation or other legacy installations.

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Abbreviations

The following abbreviations are used in this manuscript:

ACU	Automation and communication unit
AEMO	Australian Energy Market Operator
AI	Artificial intelligence
AIoT	Artificial intelligence of things
ANEEL	Agência Nacional de Energia Elétrica
ANN	Artificial neural network
AR	Autoregressive model
ARIMA	Autoregressive integrated moving average
API	Application programming interface
BGM	Bayesian Gaussian mixture
CIN	Coupling and interaction node
Cire.pl	Centrum Informacji o Rynku Energii
CNN	Convolutional neural networks
CSFs	Computational support functions
Damas	Damas Energy information system
DLM	Dynamic linear model
DRFs	Domain retrofitting functions
DTR	Decision tree regression
ECMWF	European Centre for Medium-Range Weather Forecasts
EIA	Energy Information Administration
EM-GMM	Expectation maximization Gaussian mixture model
ENR	Elastic net regression
ETS	Smoothing state space model
ES	Exponential smoothing
FAR	Functional autoregressive model
FARX	Fractional-order autoregressive model with exogenous variables
FCC	Florida Climate Center
FFANN	Feedforward artificial neural network
GBR	Gradient boosting regression
GPU	Graphics processing unit
GRNN	General regression neural network
GRU	Gated recurrent unit
HW	Holt–Winters
IEEE	Institute of Electrical and Electronics Engineers
IESO	Independent electricity system operator
IoT	Internet of things
ISFs	Interdomain support functions
JSON	JavaScript object notation
KEPCO	Korea Electric Power Corporation
KMA	Korea Meteorological Administration
KNNR	K-nearest neighbor regression

LAN	Local area network
LR	Linear regression
LSTM	Long short-term memory
MAC	Media access control
MAE	Mean absolute error
MAN	Metropolitan area network
MLP	Multilayer perceptron
MPR	Multivariate polynomial regression
MRM	Multiple regression model
MQTT	Message queue telemetry transport
NARX	Non-linear autoregressive exogenous
N-BEATS	Neural basis expansion analysis for interpretable time series
NNAR	Autoregressive neural networks
NNETAR	Neural network time series forecasts
ONS	Operador Nacional do Sistema
OPs	Operational primitives
OPSD	Open power system data
P2P	Peer-to-peer
PoI	Points of interface
PR	Polynomial regression
QoS	Quality of service
R^2	R-squared score
RAM	Random access memory
RFR	Random forest regressor
RMS	Root mean square
RMSE	Root mean squared error
RNN	Recurrent neural networks
RS	Regression with seasonality
SARIMA	Seasonal ARIMA
SCC	Supervision and control center
SLFN	Single-layer feedforward neural networks
SmartLVGrid	Smart low-voltage grids
SN	Service node
SoC	System-on-a-chip
SSD	Solid state drive
SVR	Support vector regression
TBATS	Trigonometric Box–Cox transform, ARMA errors, trend, and seasonal components
TCN	Temporal convolutional network
TCP	Transmission control protocol
TFT	Temporal fusion transformer
U.S.	United States
W	Watts
WSN	Wireless sensor network
XGBoost	Extreme gradient boosting
XGBR	XGBoost regressor

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3.4 ARTIGO 03 - SMARTLVENERGY: AN AIOT FRAMEWORK FOR ENERGY MANAGEMENT THROUGH DISTRIBUTED PROCESSING AND SENSOR-ACTUATOR INTEGRATION IN LEGACY LOW-VOLTAGE SYSTEMS [2] [3]

3.4.1 Resumo

A integração digital é essencial para a gestão eficiente e sustentável dos recursos energéticos, especialmente na modernização de infraestruturas desatualizadas. Isso envolve a incorporação de dispositivos sensores e atuadores para monitoramento e controle precisos de energia, apoiados por computação distribuída desde a borda até a nuvem, necessária para decisões analíticas e preditivas personalizadas. As estratégias de *retrofit* incorporam esses recursos em sistemas mais antigos, melhorando as infraestruturas existentes enquanto se adaptam ao progresso tecnológico. No entanto, faltam metodologias sistemáticas para a integração de sensores e atuadores na literatura. Portanto, este artigo apresenta o *framework* SmartLVEnergy, projetado para modernizar sistemas legados de baixa tensão com uma abordagem de *retrofit*, integrando sensoriamento descentralizado, controle, processamento distribuído e análises preditivas. O *framework* foi utilizado para viabilizar o *retrofit* do painel de distribuição de energia de uma planta de manufatura legada com dispositivos sensores, que suportam monitoramento remoto e análise preditiva descentralizada usando modelos para previsão de demanda de energia a cada 15 minutos baseados em redes *Long Short-Term Memory* (LSTM) de duas camadas, aderindo aos princípios da Inteligência Artificial das Coisas (AIoT) e do *Tiny Machine Learning* (TinyML). Comparado com modelos LSTM de única camada e não quantizados para a previsão de demanda de energia da instalação, entre 8 de maio e 11 de julho de 2023, nossa abordagem mostrou redução na latência de previsão e no consumo de memória. O disjuntor principal apresentou métricas de R-quadrado (Rš) de 96,67% e Erro Quadrático Médio (RMSE) de 7,23 kW, com o sensor associado mostrando uma latência de previsão de 54,55 ms e utilizando 58,45 KB de memória FLASH. Essas métricas para o sensor de melhor desempenho foram 97,33%, 0,39 kW, 5,55 ms e 10,20 KB. Este *framework* de AIoT marca um avanço significativo no *retrofit* de sensores e atuadores, mesclando tecnologia digital com sistemas legados para uma gestão inteligente de energia.

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3.4.2 Revista

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3.4.3 Corpo Editorial

- Prof. Dr. Zeynep Celik. Electrical Engineering Department. University of Texas at Arlington, USA.
- Prof. Dr. Huang Chen Lee. Department of Communications Engineering. National Chung Cheng University, Taiwan.

3.4.4 Publicação

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SmartLVEnergy: An AIoT Framework for Energy Management through Distributed Processing and Sensor-Actuator Integration in Legacy Low-Voltage Systems

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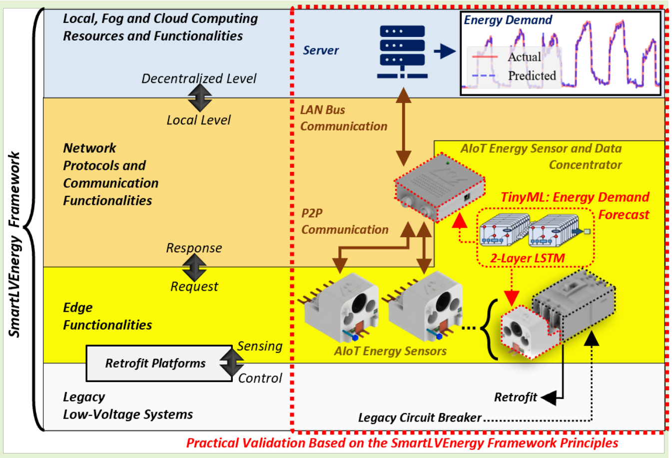

***Abstract*—** **Digital integration is essential for efficient and sustainable management of energy resources, especially in modernizing outdated infrastructures. This involves embedding sensor and actuator devices for precise energy monitoring and control, supported by distributed computing from edge to cloud, necessary for tailored analytical and predictive decisions. Retrofit strategies incorporate these resources into older systems, enhancing existing infrastructures while adapting to technological progress. Nevertheless, systematic methodologies for sensor-actuator integration are lacking in the literature. Therefore, this article introduces the SmartLVEnergy framework, designed to modernize legacy low-voltage systems with a retrofitting approach, integrating decentralized sensing, control, distributed processing, and predictive analytics. The framework was employed to retrofit the energy distribution panel of a legacy manufacturing plant with sensor devices, which support remote monitoring and decentralized predictive analysis using 15-minute energy demand forecast models based on 2-layer Long Short-Term Memory (LSTM) networks, adhering to Artificial Intelligence of Things (AIoT) and Tiny Machine Learning (TinyML) principles. Benchmarked against non-quantized and single-layer LSTM models for the installation energy demand forecast between May 8 and July 11, 2023, our approach showed reduced prediction latency and memory consumption. The main circuit breaker exhibited a 96.67% R-squared score (R^2) and 7.23 kW Root Mean Squared Error (RMSE), with the associated sensor showing a prediction latency of 54.55 ms and using 58.45 KB of FLASH memory. These metrics for the best-performing sensor were 97.33%, 0.39 kW, 5.55 ms, and 10.20 KB. This AIoT framework marks a significant advancement in sensor-actuator retrofitting, blending digital technology with legacy systems for intelligent energy management.**

***Index Terms*—** **AIoT, demand forecasting, retrofit, sensor-actuator system integration, SmartLVEnergy Framework, SmartLVGrid Metamodel, TinyML.**

I. Introduction

THE convergence of the Internet of Things (IoT) and Artificial Intelligence (AI) is increasingly contributing to the advancement of sustainability and energy management across diverse applications, thereby yielding substantial socio-economic benefits. Implementations grounded in these technologies facilitate, for instance, the integration of intelligent tools within Smart Environment systems for predictive analysis of energy consumption and circuit monitoring. This integration serves to optimize energy utilization and mitigate wastage, all from a demand-side perspective [1]–[3].

To confer tangible and enduring benefits, concerted efforts must be directed toward the cost-effective revitalization of legacy installations, addressing the challenge of modernizing their infrastructures to align with the demands of the digital age. Transitioning existing installations to energy-efficient Smart Environments requires advanced systems capable of dynamic energy management. This entails the integration of sensor and actuator networks to gather real-time data and enable

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real-time control strategies. These strategies should be built on a strong foundation that merges statistical methodologies for forecasting and the capabilities of Machine Learning techniques for pattern recognition and adaptive decision-making [4]. Acknowledging the need for sophisticated management in the electrical sector, Artificial Intelligence of Things (AIoT) emerges as a promising route for modernization. By integrating predictive analytics with data from interconnected sensors, AIoT unlocks innovative solutions for real-time remote monitoring and analysis. This fusion of AI and IoT provides groundbreaking opportunities for optimizing energy consumption, ensuring grid reliability, and advancing proactive maintenance strategies [5].

While smart technologies possess considerable potential for diverse fields, transitioning current infrastructures to these systems is a significant challenge. Extensive hardware upgrades often pose an impractical and cost-prohibitive barrier, further compounded by limitations associated with complete technological replacement. Addressing these constraints necessitates innovative approaches that leverage existing hardware capabilities while seamlessly integrating smart technology functionalities [6]. Adding to this challenge is the difficulty in obtaining accurate energy data, which is crucial for evaluating these installations, frequently hampered by the absence of adequate technology for consistent data collection [7]. In developing countries, for context, this problem is especially acute in legacy consumer units, where effective sensing, control and predictive resources are often elusive [8]. Furthermore, the widespread use of pollutant-intensive energy sources in these regions aggravates environmental concerns [9].

Implementing sudden technological changes in existing infrastructure can carry significant economic impacts, potentially impeding the adoption of new features. Therefore, it is vital to develop well-conceived, systematic strategies to effectively manage this transition. Retrofitting is recognized as an effective strategy to update legacy infrastructures, thereby enhancing the management of critical resources. Retrofit interventions facilitate the digital upgrade of consumer units and circuits by integrating sensors and actuators at essential interfacing points [10]. However, the effectiveness and extensibility of retrofitting hinge on a well-conceived architectural framework that sets forth essential principles, aligns interface protocols with existing infrastructures and secures data network interoperability. Whereas current literature does not offer comprehensive frameworks for these purposes, it references the SmartLVGrid metamodel as an exemplar for updating legacy circuits in the low-voltage energy distribution domain to meet Smart Grid standards [11]. This metamodel encompasses the standardization of interfaces, both physical and logical, which are fundamental to systematizing control, sensing, and data traffic strategies from legacy systems to supervision centers.

Within the context of Smart Environments, where legacy infrastructure poses challenges to implementing advanced technologies, Cloud computing presents a compelling approach for establishing decentralized supervisory centers. By offloading computational and storage demands onto the Cloud, this solution overcomes hardware limitations while offering flexibility and scalability for diverse monitoring and control needs [12]. Nevertheless, the economic feasibility of cloud-based energy management solutions can vary significantly among different communities. The costs associated with intensive and continuous use of cloud services may render these smart solutions financially impractical in certain scenarios [13]. Depending on the required complexity of resources, those initially designated for cloud implementation may be alternatively deployed on fog servers or directly onto the sensor devices, a process referred to as Edge Computing [14]. Grounded in the principles of distributed systems, this approach harnesses shared computational capacity to minimize reliance on centralized architectures, thereby mitigating potential failure risks [15]. By facilitating on-device data processing, Edge Computing enables near-real-time analysis, minimizing both latency and the demand for high-bandwidth networks and powerful central computing resources. This distributed paradigm fosters enhanced responsiveness and resource efficiency, paving the way for scalable and resilient data processing across geographically dispersed networks.

The trend for predictive solutions in these scenarios considers the adoption of Tiny Machine Learning (TinyML) which aligns with AIoT implementations on cost-effective embedded systems with limited processing and storage capacities in conjunction with sensor technology [16]. Such a strategy provides a streamlined and scalable pathway to update legacy systems with predictive functionalities, circumventing the need for extensive modifications or significant financial outlays.

The integration of decentralized computing and digital solutions holds substantial promise for optimizing energy management in legacy systems. Central to this integration is the standardization of physical and logical interfaces, particularly through retrofit strategies. The SmartLVGrid, with its standardized interfaces for upgrading low-voltage distribution systems, exemplifies this approach. However, there is a need for a framework that not only transcends the initial scope of SmartLVGrid but also leverages its groundwork to facilitate IoT and AIoT implementations, enhancing energy management in industries, buildings, and consumer units.

The goal of this paper is to introduce and demonstrate the effectiveness of the SmartLVEnergy framework, leveraging Cloud, Fog, and Edge Computing functionalities to tailor energy management to the specific requirements of a given infrastructure. To this end, sensor devices were developed and installed on an energy distribution panel at a router manufacturing plant in Manaus (Brazil), following the proposed framework. Specifically, the legacy system comprises the main circuit and associated circuits of the factory's power distribution board, lacking intelligent circuit breakers. This system was selected due to issues with exceeding energy demand and resulting fees based on national legislation. Importantly, the factory lacked existing IoT or AIoT solutions, classifying it as a legacy installation. Similar challenges are prevalent in other legacy systems globally, including homes, buildings, and industries.

Our approach enabled remote monitoring of each circuit, as well as the main energy bus of the installation. To enhance energy management and adhere to the Brazilian standards set by the National Electric Energy Agency (ANEEL) [17], each

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retrofit device was outfitted with a TinyML model for forecasting short-term (15 min ahead) energy demand. These models employed quantized 2-layer stacked recurrent neural networks based on Long Short-Term Memory (LSTM) architecture. The performance of these models was evaluated focusing on memory consumption, latency, and accuracy, by comparing them against their non-quantized equivalents and single-layer LSTM counterparts. Each model was trained using the dataset derived from the same monitored circuits in the panel. This approach enables real-time monitoring and forecasting, aiding in decisive actions for energy management in legacy low-voltage systems.

This paper makes the following key contributions:

1) Introducing SmartLVEnergy, a comprehensive AIoT framework to integrate retrofit solutions and distributed computational functionalities for energy management in legacy low-voltage systems;
2) A practical implementation of a sensor system model according to the proposed SmartLVEnergy framework to enable energy demand monitoring and forecasting in legacy circuits, utilizing TinyML principles;
3) A comparative performance analysis of quantized and non-quantized LSTM models aimed at forecasting energy demand in legacy building circuits.

This paper is organized as follows. Section II provides a survey of the state of the art related to the topic. Section III elucidates the concepts underlying the SmartLVEnergy framework. Section IV introduces a system model for demand monitoring and forecasting in legacy building circuits, based on the SmartLVEnergy framework. In Section V, the methodology employed for the implementation and evaluation of the proposed system is detailed. Section VI discusses the results obtained and Section VII presents conclusions and proposals for future work.

II. Related Work

A. Context

This paper aims to bridge a significant gap in the literature concerning advanced energy management in low-voltage systems, building upon previous research by these and other researchers [11], [18], [19], [20]. The scope of SmartLVGrid covers the transition from legacy electrical energy distribution networks towards the smart grid paradigm. In a previous paper, [18], we employed SmartLVGrid primitives and protocols to upgrade the lighting system of a legacy building installation by retrofitting existing luminaires and inserting monitoring, control, and communication resources. In another study [19], we presented a similar strategy to enable the monitoring and energy management of a legacy building installation through the retrofit of legacy circuit breakers with IoT sensor solutions. In a later publication [20], building upon the advancements in IoT hardware and communication from [19], we introduced an approach to enhance a pre-existing installation. This involved implementing real-time monitoring through sensor-retrofitted legacy circuit breakers and incorporating AIoT capabilities. Additionally, we forecasted energy demand for a manufacturing facility and its associated legacy circuits, thereby integrating predictive intelligence through a retrofit approach utilizing data collected from sensor devices.

Although previous research has made substantial contributions to the field, it is essential to articulate the differences between this study and earlier efforts. In reference [20], the SmartLVGrid metamodel [11] was utilized to develop a system capable of predicting energy demand based on sensor data. This paper builds upon that foundation by enhancing the SmartLVEnergy framework. It not only incorporates the primitives of the SmartLVGrid metamodel but also facilitates the distributed processing of energy data from legacy systems. This adaptation reduces reliance on centralized computing and network infrastructure for energy data analysis in legacy systems. Furthermore, while the methodology was previously validated in a real-world router manufacturing facility (as in [20]), the present study introduces innovations such as short-term energy demand forecasts conducted directly on the sensors. This capability enables distributed processing of critical energy management information in existing installations using retrofit sensor elements. Consequently, this framework offers a systematic avenue for developing TinyML solutions that are applicable to a broad spectrum of low-voltage electrical systems in urban, industrial, residential, and commercial settings, enhancing the versatility of the SmartLVGrid metamodel. Importantly, our approach is both sustainable and cost-effective, preserving existing infrastructure like cables and circuit breakers, thereby serving as a model for sustainable energy management across diverse environments.

B. Frameworks in Smart Energy Management

Research in this field presents various methodologies for predicting energy demand and consumption in consumer units, utilizing real-time data, cloud and fog computing resources [21], [22]. These methodologies range from statistical techniques to Machine Learning models, chosen based on data complexity, dimensionality, and nonlinearity. In complex scenarios, Deep Learning models, especially LSTM networks, become critical for forecasting energy demand over varying periods.

Some works explore both the use of Machine Learning and Statistical approaches in energy forecasting within residential and commercial buildings [23], [24]. Additional studies demonstrate LSTMs' effectiveness in various settings [25]–[27]. Despite their robustness, the context-specific nature of these models hinders their integration into diverse systems due to the lack of standardized adaptation methodologies and often-limited data handling capabilities or data repositories in legacy settings, thus highlighting a critical gap in enabling their widespread adoption.

Beyond cloud and fog solutions, a promising approach is shifting towards edge-based solutions, enhancing efficient localized data processing [28]. Recent literature emphasizes energy predictive models tailored for edge computing systems. A methodology was introduced for training, compressing, and evaluating energy forecasting models using the Raspberry Pi platform and residential building data [29]. Dalai et al. (2019) [30] utilized Machine Learning on the Raspberry Pi as an edge

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device to compare real-time energy consumption predictions with cloud-based computing, demonstrating faster prediction times with edge-based computing for real-time energy consumption forecasting. Tran and co-authors (2022) [31] detailed a technique for forecasting photovoltaic energy output a day ahead, leveraging meteorological data. They utilized data from solar and weather instruments using stacked LSTMs, optimized for edge servers and validated on the Jetson Nano platform. Moreover, an edge-AI-based forecasting was introduced by Lv et al. (2022) [32] for short-term electricity in smart microgrids, analyzing datasets from Belgium and China.

Despite the performance comparisons detailed in the existing literature, which demonstrate the viability of cloud, fog, and edge computing solutions for energy analysis and forecasting, other studies take a broader approach through intelligent energy management frameworks that are applicable across various sectors with sensor and actuator components, as well as the distributed processing of energy information. Table I compares existing frameworks for energy management across different applications.

In [33], the authors proposed an energy management framework leveraging cloud-based and IoT technologies for energy distribution networks in Smart Cities. They reduced operational costs by optimizing load consumption patterns and alternative energy generation based on market prices, with decentralized decision-making near loads and energy sources, including at the Distribution System Operator. Paper [34] introduced an energy management framework for the industrial sector utilizing IoT and big data for data processing, storage, and visualization. This approach provides a flexible methodology allowing industries to select the most suitable IoT platform (such as AWS, Azure, Google, IBM, or Oracle) based on their specific needs and realities. In [35], the authors conducted a literature review focusing on energy management frameworks for Smart Buildings employing deep learning algorithms. The review covered topics including alternative energy sources, load control, cost reductions, performance improvements, and practical implementations. In [36], the researchers proposed an intelligent energy management framework for Smart Grids, homes, and industries, incorporating edge device solutions for real-time energy management in communication with a cloud-based supervisory center. This framework includes energy forecasting capabilities to support decision-making processes. Study [37] emphasized the importance of industrial energy management and introduced a conceptual framework based on IoT features, data analytics, and Big Data to acquire energy data.

Other research papers demonstrate practical approaches to validate proposed frameworks through sensor-based, communication, and control solutions. For example, in [38], a framework was proposed for demand-side energy management in Smart Grids using IoT and Cloud resources to generate and remotely share consumer profiles and loads with energy companies or consumers. Similarly, in [39], a middleware solution was implemented for demand-side energy management, focusing on the interoperability of sensor and actuator elements for energy monitoring and control. In [40], a framework was presented for sustainable demand-side energy management based on digital twins, AI, and IoT, offering consumer recommendation and evaluation services and load behavior prediction to enhance energy efficiency. Lastly, in [41], a framework was developed for smart energy management devices integrating software, hardware, and communication resources with existing energy meters using a retrofit approach. Predictive energy demand capabilities were incorporated using Linear Regression (LR), extreme Gradient Boosting (XGBoost), and LSTM algorithms on a microcomputer.

Despite significant advancements in frameworks for energy management, prior studies have generally lacked systematic methodologies and real-world implementations on real-time sensor and control devices within legacy electrical systems. Moreover, these studies have not sufficiently explored the development of specialized sensing and control solutions, or the generic retrofit interfaces for integration or distributed processing and analysis of energy data with existing systems. This highlights a critical need for focused research to enhance interoperability and functionality in energy management technologies. The prevailing literature often overlooks the challenge of integrating AIoT solutions into legacy installations for energy prediction in residential, commercial, or industrial settings. Studies on the retrofitting and modernization of existing systems have primarily focused on using processing platforms as edge servers for proposed prediction tasks. In scenarios where designing sensor elements with on-site intelligence for real-time processing is considered, TinyML solutions offer economic, security, privacy, bandwidth, offline prediction, on-device analytics, and latency advantages. Nevertheless, despite these benefits, none of the cited works have incorporated TinyML into their proposed frameworks. The SmartLVEnergy framework aims to address this gap by offering a comprehensive and systematic approach to modernizing these legacy systems to improve energy management.

C. TinyML in Energy Management

TinyML enhances energy management through advanced predictive functions in microcontroller-based sensors, necessitating efficient optimization like quantization to minimize computational load [42], [43]. Review articles have explored TinyML applications in environmental scenarios and areas like image recognition and biomedical signal processing [44], [45], but energy consumption or demand prediction intersecting with TinyML remains underexplored in their studies. There were notable exceptions in which TinyML was applied for forecasting photovoltaic energy at varying intervals, demonstrating its feasibility on the ESP32-S3 and STM32F3 microcontrollers, respectively [46], [47]. Similarly to this paper, Hayajneh et al. (2024) [46] employed a two-layer stacked LSTM for energy prediction. Nevertheless, the authors worked with photovoltaics rather than focusing on energy monitoring sensors embedded in low-voltage systems.

Our study centers on the integration of TinyML to enhance energy efficiency and sustainability in legacy systems. This includes designing systemic and intelligent retrofit solutions, and ensuring smooth digital integration while adhering to the constraints of existing network and electrical infrastructures.

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TABLE I: Comparison of frameworks for energy management

Work	Year	Applications	IoT	Distributed Processing	AIoT	Practical Implementations	Sensor-Application Interoperability	Sensor-Actuator Integration	Retrofit Approach	TinyML Sensors
[33]	2020	Smart Cities	[X]	[X]						
[34]	2021	Smart Industries	[X]			[X]				
[35]	2021	Smart Buildings	[X]		[X]					
[36]	2021	Smart Grids, Homes, Industries	[X]	[X]	[X]	[X]				
[37]	2021	Smart Grids, Homes, Buildings, Industries	[X]	[X]		[X]	[X]	[X]	[X]	
[38]	2022	Smart Grids, Homes, Buildings, Industries	[X]	[X]		[X]	[X]	[X]	[X]	
[39]	2022	Smart Industries	[X]							
[40]	2024	Smart Grids, Industries	[X]		[X]					
[41]	2024	Smart Grids	[X]		[X]	[X]	[X]	[X]	[X]	

III. SmartLVEnergy Framework

SmartLVEnergy enhances low-voltage energy systems with adaptable protocols and interfaces, facilitating advanced energy management. It integrates sensors and actuators with bespoke communication protocols to provide comprehensive AIoT capabilities. The integration of our framework with existing infrastructures relies on retrofit platforms, which are sensors and actuators capable of being added to pre-existing systems for control and monitoring tasks. The development and resources of these devices are guided by the specifications of the Automation and Communication Unit (ACU) described in the SmartLVGrid metamodel. This ACU acts as the middleware, forming the lowest layer of the metamodel, and includes operational primitives like DRFs, CSFs, and ISFs (described in the SmartLVGrid metamodel section). Computational Support Functions (CSFs), which manage computational resources such as information storage and processing, can also incorporate edge processing capabilities like machine learning-based predictive models. This aspect, although not explicitly outlined in the SmartLVGrid metamodel, defines which processing or predictive functionalities can be integrated via retrofit platforms. By utilizing this approach, part of the processing typically handled on a local server, in the cloud, or fog, is instead executed at the edge. Additionally, the "Local, Fog, and Cloud Computing Resources and Functionalities" layer can leverage distributed computing resources based on available capacities and requirements, thereby reducing centralized computational demands. Moreover, functions needed to facilitate sensor and actuator interoperability with the supervisory center can be implemented using communication functionalities and network protocols.

Our framework stands out in its ability to ensure network and electrical installation compatibility, while leveraging the potential of Cloud, Fog, and Edge Computing, including TinyML applications for energy management. SmartLVEnergy thus marks a significant advancement in the field, bridging the divide between cutting-edge predictive analytics and practical, sustainable energy management solutions for legacy low-voltage systems. This approach enhances energy efficiency and aligns with global sustainability goals [48], marking a major step forward in the digital transformation of energy management practices.

Figure 1 depicts the SmartLVEnergy framework stack.

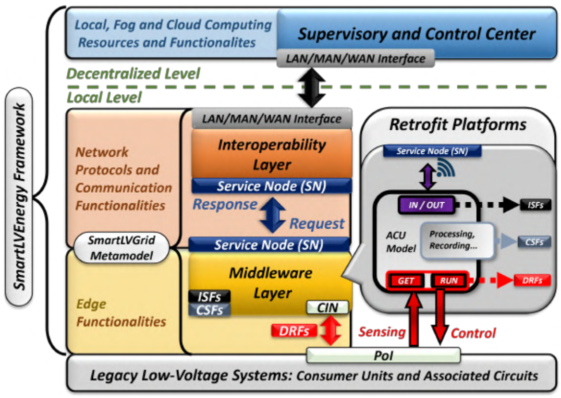

Fig. 1: SmartLVEnergy framework.

As previously discussed, the SmartLVEnergy framework is designed to enhance the SmartLVGrid metamodel implementation and complement prior research by these authors [18], [19], [20] with energy data processing and analytics adjacent to legacy systems, thereby facilitating the automation and enhancement of energy management. By enabling the allocation of distributed computational to legacy infrastructures and their associated circuits, this framework facilitates decentralized energy management, leveraging prediction, sensing, control, storage, and data processing capabilities.

Further details on its components and applications are discussed in the following subsections.

A. SmartLVGrid Metamodel

SmartLVGrid facilitates digital upgrades, enhancing existing structures with Operational Primitives (OPs) [11]. Utilizing systems engineering and retrofitting, it merges electronic and computational technologies for improved sensing, control, and communication in existing infrastructures. The metamodel consists of two main layers, middleware, and interoperability, as illustrated in Figure 1.

The SmartLVGrid metamodel's legacy layer (Figure 1) is modernized through Points of Interface (PoIs). The middle-

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ware layer, connected to the Legacy layer via Coupling and Interaction Nodes (CIN), implements Domain Retrofitting Functions (DRF) for control and data gathering. This layer includes other two OPs: Computational Support Functions (CSF) for data operations and Interdomain Support Functions (ISFs) that facilitate communication through Service Nodes (SN). The SNs ensure the middleware layer communication and cross-platform compatibility within legacy systems via the interoperability layer.

1) Middleware Layer: The middleware layer serves as the intermediary between legacy systems and SmartLVGrid's innovations, enabled by retrofit platforms containing sensors and actuators. These devices, known as Automation and Communication Units (ACU) (Figure 1), feature the "In/Out" port for the ISFs implementation, and the "Get" and "Run" ports for the DRFs. Through CSFs, the ACUs integrate processing and storage capabilities, adding local intelligence to the legacy layer. This study aims to apply predictive models as a CSF feature from a SmartLVEnergy perspective.

2) Interoperability Layer: This layer acts as the communicative core, interfacing with the Supervisory and Control Center (SCC) of the legacy system within Local or Metropolitan Area Networks (LAN/MAN). It specifies the communication rules among ACUs using communication standards and protocols for the existing infrastructure. This layer structures a data network, assigning hierarchical roles to ACUs as coordinators or operators. In expanded systems, it allows the inclusion of sub-coordinator ACUs, enhancing efficiency and real-time decision-making in distributed setups. In this study, Wide Area Networks (WAN) were introduced as an alternative for communication interfaces in the interoperability layer.

B. Local, Fog and Cloud Computing Resources and Functionalities

The SmartLVEnergy framework employs an integrated suite of local, fog, and cloud computing functionalities and resources to implement and enhance the operational efficiency of the SCC. By leveraging local computing, the framework ensures immediate response and stringent data privacy for real-time analytics and control tasks directly at or near consumer units, thereby minimizing latency and reducing reliance on external networks. Fog computing further enhances this capability by bringing computing, storage, and networking services closer to end devices, improving data management, and application reliability across distributed systems with reduced latency. Meanwhile, cloud computing offers expansive storage and robust processing power, enabling the SCC to undertake extensive data sharing, sophisticated information processing and to harness advanced analytics.

This framework allows for the sharing of these computational functionalities, effectively distributing the computational load to maximize operations based on the needs and availability of legacy systems. Additionally, all these resources contribute to the energy management of existing installations using data from retrofit solutions, and also in controlling installation loads, depending on the available resources.

C. Network Protocols and Communication Functionalities

This component is dedicated to communication protocols that enable interoperability among retrofit platforms within the middleware layer. These protocols are crucial for facilitating the sending of requests and receiving responses from the SCC. The communication protocols, along with the structure and encapsulation of transmitted messages, must be developed in line with existing communication standards and topologies suitable for the installation to maximize the use of the pre-existing communication network infrastructure, where SNs are utilized as access parameters to the data network. Moreover, this layer also enables communication functionalities, such as over-the-air (OTA) firmware updates for retrofit platforms.

D. Edge Functionalities

The edge functionalities delineate the processing capabilities that can be implemented through retrofit platforms. This includes the integration of processing tasks with sensor and actuator devices, and executing or training machine learning models in proximity to the legacy layer. This proximity enhances decision-making processes, as it allows for direct action without relying on network infrastructures to relay data to the control and supervision center, which typically requires internet access and further data processing. Besides reducing latency, this layer offers a framework for implementing AIoT functionalities at the edge that can facilitate the deployment of applications like TinyML, advancing intelligent energy management in legacy installations.

IV. A SmartLVEnergy System for TinyML-Based Demand Forecasting in Legacy Circuits

This section presents a system based on the SmartLVEnergy framework principles to demonstrate its effectiveness in incorporating AIoT features using distributed computing and sensor integration in an existing manufacturing environment. The proposed system addresses the requirements and challenges discussed in the following subsection.

A. Problem Description

The SmartLVGrid metamodel has transcended its original utility in energy distribution, finding diverse applications. Its adaptability is evident in retrofitting building lighting for Smart Building integration [18] and advancing the digitalization of building and industrial circuits for superior energy management, integrating real-time monitoring and predictive demand forecasting [19], [20]. These developments align with ANEEL regulations in Brazil, where consumer units on medium or high-voltage grids face tariffs based on consumption and predetermined demand within 15-minute intervals [17], with penalties for exceeding contracted demand.

As previously mentioned, studies [18]–[20] extended the SmartLVGrid metamodel with the SmartLVEnergy framework's principles. They encountered network and computational constraints that required systemic adaptations to make the most of existing resources. Although vital for oversight,

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storage, and processing, the continuous use of cloud and fog computing in industrial environments may incur significant costs and prove inappropriate for conventional consumer units. Further impediments include:

1) Need for continuous high-speed internet and a sturdy secure network for ongoing energy management;
2) Delays in real-time feedback, leading to risks of delayed or suboptimal actions and impacting vital operations;
3) Exposure to disruptions due to technical or administrative issues with cloud or network service providers.

In emerging societies, legacy structures confront such challenges. Yet, with the TinyML approach, prediction algorithms can be integrated into sensors that monitor these infrastructures, enabling sophisticated on-device analytics. Whereas refining these models, especially through quantization techniques, might occasionally affect prediction accuracy, it supports offline forecasting, and bolsters data-driven decision-making, all whereas reducing dependence on complex networking and costs associated with cloud, fog, and edge servers.

To address these issues, we propose a retrofit approach aligned with the SmartLVEnergy framework principles, equipping sensor devices with predictive capabilities for energy demand forecast in the entire building and key circuits. Building upon existing literature contributions [20], we utilize decentralized computing to reduce dependence on cloud and fog-based forecasting methods in the legacy infrastructure monitored. In compliance with ANEEL guidelines, our assessment contrasts embedded quantized models with their non-quantized equivalents over a 15-minute interval, focusing on performance, prediction latency and memory consumption.

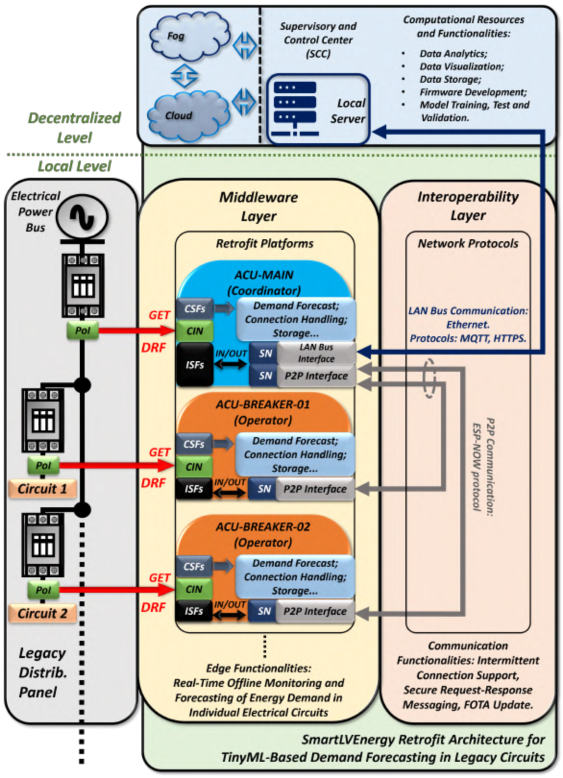

Fig. 2: Proposed AIoT system.

B. System Architecture Definitions

The AIoT system architecture from the SmartLVEnergy framework in Figure 2 is an enhancement of prior work [20]. It enables energy demand forecasting for legacy installations and their circuits using edge functionalities in sensor devices.

The proposed system architecture streamlines the implementation of SmartLVGrid metamodel operational primitives, adhering to the component structure of the SmartLVEnergy framework. Central to this architecture is the middleware layer, which involves the integration of retrofit platforms, notably the ACU-MAIN. This element acts as a coordinator, interfacing with the main circuit breaker of existing distribution panels and communicating with operational devices, specifically ACU-BREAKERs, coupled with the remaining legacy circuits.

As DRFs, both ACUs acquire and process electrical parameters. This capability is intrinsically linked to their "Get" port. Among the CSFs of these ACUs, the storage of configuration parameters in data networks and the management of connections in this specific network stand out. As for the ISFs, they manage and process both requests and responses within the network they belong to, using their "In/Out" ports. The ACU-MAIN has two communication interfaces, one Peer-to-Peer (P2P) and another Local Area Network (LAN) Bus, used for interactions both with the ACU operators and the local server, respectively.

Unlike previous research, the ACUs now embed AI capabilities to enable demand energy forecasting as a primary CSF. A key feature of this architecture is its emphasis on Edge Computing functionalities, demonstrated through the application of ACUs that enable real-time monitoring and predictive analytics of energy demand. By retrofitting at the local level, close to existing circuitry, the system's capability in smart energy management is significantly enhanced. Another significant aspect is the detailed specifications for the interoperability layer, implemented via Network Protocols and the proposed Communication Functionalities. Among these, is the establishment of an intermittent data network communication structure, ensuring secure exchanges of request and response messages. Additionally, it is important to note the inclusion of support for over-the-air firmware updates (FOTA), enabling dynamic model updates and adjustments for future contingencies. This architecture, therefore, offers considerable flexibility in various contexts, allowing for systematic, structured reconfiguration or expansion through the modification or addition of interfaces and resources, including the integration of updated predictive models into the device firmware.

Located on the installation's local server, the SCC operates at a decentralized level within the architecture. It serves as a hub for the deployment and management of computational resources, essential in optimizing energy management. This

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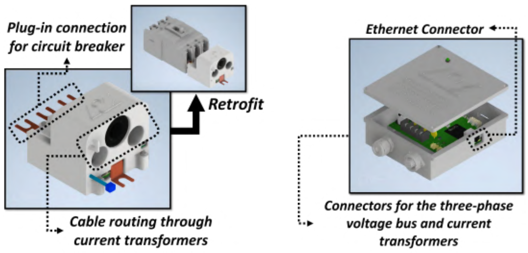
includes the deployment of Data Analytics, Visualization, Storage, and Firmware Development functionalities, encompassing training, testing, evaluation, and the development of learning models for the ACUs. At the SCC, demand forecasting algorithms for the subsequent 15-minute period are developed, in alignment with ANEEL guidelines and leveraging energy data from the devices. Additionally, the architecture offers the capability to connect the SCC with cloud or fog computing services, facilitating interaction among these services for geographically distributed computational functionalities. However, this aspect of linking with cloud or fog services will not be a focus of evaluation in this study.

Sections IV-B.1 and IV-B.2 delve into the retrofit platforms and network protocol specifications within the proposed architecture to clarify the physical and logical interfaces.

1) Retrofit Platform Specifications: The retrofit sensor solutions were installed on the power distribution panel of a legacy manufacturing facility situated in the industrial hub of Manaus, Amazonas, Brazil. The chosen plant, a router factory, encountered occasional challenges with exceeding energy demand and aimed to comply with ANEEL regulations [17]. As part of the proposed framework, the suggestion is to individualize this prediction process within sensor devices. The characteristics of the developed devices are further detailed in [19], [20]. Figures 3a and 3b respectively showcase the physical attributes of the ACU-BREAKER and ACU-MAIN. As depicted, the ACU-BREAKER was designed to be compatible with three-pole thermomagnetic circuit breakers, capturing the voltage from each pole. Additionally, it features three current transformers, facilitating cable routing to the breaker. This allows for a retrofit in the facility's circuits in a less intrusive manner with minimal visual clutter since the devices will be installed internally in the industry's panel.



(a) (b)

Fig. 3: ACU-BREAKER (a) and ACU-MAIN (b).

The ACU-MAIN has connectors that accommodate current transformers and terminals that collect the voltage from the three-phase busbar of the installation. Therefore, it does not attach to the breaker like the ACU-BREAKER. Moreover, it comes with an Ethernet connector, used to communicate over a LAN with the local server.

Both devices internally incorporate components for surge protection, voltage and current channel conditioning, and the Analog Front-End ADE7758 for accurate digitization of the acquired electrical parameters. As a processing and communication unit, these devices integrate the System on Chip (SoC) ESP32 from the manufacturer Espressif.

2) Network Protocols Specifications: SmartLVEnergy underscores the need to align existing networks and resources to facilitate the modernization of current systems. As elucidated in [49], legacy network infrastructures might grapple with challenges introduced by new connection-oriented communication technologies for the internet. Hence, binding sensor devices to TCP or UDP-based protocols in legacy network infrastructures may impede the integration of smart devices in certain scenarios. Although IPV6 emerges as a solution for connecting more devices compared to IPV4, developing nations like South Africa point to hurdles in integrating IPV6 into their older networks, encompassing costs, incompatibilities, and political challenges [50].

From this viewpoint, non-IP connections can be a feasible path for integrating retrofit solutions into some legacy infrastructures. Both Bluetooth Low Energy and the ESP-NOW protocol are highlighted alternatives in the literature. ESP-NOW, coexisting with WiFi and Bluetooth on the ISM 2.4 GHz band, is prominent for its multi-hop, lightweight, secure, and self-sustainable wireless communication. Exclusive to Espressif manufacturer devices, this protocol operates atop the MAC layer of the IEEE 802.11 standard, devoid of an IP connection requirement. Utilizing vendor-specific action frames, it transmits data directly between devices using MAC addresses [51]. This approach enhances scalability and agility, streamlining communication immediately post-initialization, and negating prolonged pairing requirements. Such a feature is pivotal during power supply interruptions when energy sensors necessitate swift reconnection post-reboot. Additionally, this protocol endorses FOTA updates for compatible devices.

Thus, we chose to facilitate interoperability using P2P interfaces, employing the ESP-NOW protocol for communication between the ACU-BREAKERs and the ACU-MAIN. This strategy bypasses the legacy network infrastructure, minimizing IP connections and potential network overload. Our proposal also features an Ethernet interface for the ACU-MAIN to link with a local server, utilizing the efficient MQTT protocol with QoS 0, which is known for its lightweight structure and reliable transmission in low-bandwidth scenarios [52]. This Ethernet approach was recommended by the studied industry's engineering team.

After selecting the protocols, we implemented and validated the ISFs discussed in section IV-B. Notably, the SNs shown in Figure 1 serve as unique credentials allowing ACUs to interact across various interfaces. Ethernet interface credentials pertain to installation network parameters and target application addresses. In contrast, for the P2P interface, the credentials are linked to the ESP32 MAC Address of the ACUs, facilitating communication via the ESP-NOW protocol.

The system's communication operations proceed as follows: every minute, the ACU-MAIN collects and processes electrical parameters from the installation's main electrical bus and then requests data processed from the ACU-BREAKERs using the ESP-NOW protocol. Data are then forwarded to the local server using MQTT. Additionally, the ACU-MAIN can receive firmware updates via HTTPS and distribute them to the ACU-BREAKERs through ESP-NOW.

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V. Experimental Scenario

This section explores the integration of the developed sensor devices and the application of data analysis and Machine Learning to enable efficient energy management in the legacy low-voltage circuits of the proposed SmartLVEnergy system.

A. Installation of the Proposed System

After the initial definitions, the ACUs were manufactured, set up, tested, calibrated, and then installed. Calibration was crucial to ensure the measurement accuracy stayed within a 1% margin of error. For this, we utilized a high-precision three-phase source to adjust the internal registers of the ADE7758. The industrial panel under investigation operates with a phase-to-neutral voltage of 127 V_{rms} and comprises 22 circuits. Figure 4 showcases the ACUs, installed consistently with the proposed architecture. It's pertinent to note that the ACU-BREAKER associated with the first circuit breaker experienced malfunction during the evaluation phase and has been excluded from this study's analysis.

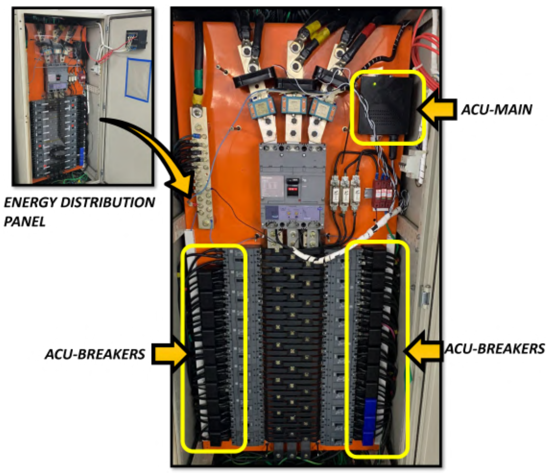

Fig. 4: ACUs integrated into an energy distribution panel.

B. Experimental Data

With the installation of the ACU-BREAKERs and the ACU-MAIN in the distribution panel, we initiated minute-by-minute data collection on parameters such as active energy, power factor, root mean square (RMS) voltage, and current across all circuits, encompassing the main breaker. The variables and their descriptions within the dataset are itemized in Table II. The dataset, industry-owned and devoid of missing values, can be made available upon request.

A previous work offers preliminary observations on energy demand spanning January 15 to April 12, 2023 [20]. A Pareto analysis isolated the top 80% energy-consuming circuits for the duration, anchoring the demand forecasting study to the most significant load contributors relative to the installation's overall demand.

TABLE II: Data variable description.

Variable	Description
Identification	Monitored circuit identification.
MAC	MAC address of installed ACU.
Timestamp	Timestamp of samples (datetime format).
Power factor	Power Factor of each circuit (%).
Active energy	Active energy of each circuit (Wh).
RMS current	RMS current of each circuit (A).
RMS voltage	RMS voltage of each circuit (V).

Table III delineates the seven circuits accounting for roughly 79.6% of the total energy consumption within the installation, elaborating on the energy consumption and the proportional impact of each load. Next, we processed the active energy to ascertain the energy demand of each circuit at 15-minute intervals. Based on this, a total of 6,782 data points of demand were considered for analysis for each dataset corresponding to each circuit. This evaluation facilitated a deeper understanding of the demand patterns for the circuits identified in Table III.

TABLE III: Major circuits and their energy consumption.

Identification	Load	Energy	Impact
Circuit 13	Central Air - 02	23.6 MWh	18.4%
Circuit 16	Central Air - 03	18.5 MWh	14.4%
Circuit 10	Central Air - 01	15.5 MWh	12.1%
Circuit 8	Server 02	15.0 MWh	11.7%
Circuit 6	Production	10.6 MWh	8.2%
Circuit 12	Administration	10.0 MWh	7.8%
Circuit 14	Stock 01	8.9 MWh	7%
Total	-	102.1 MWh	79.6%

Figure 5 presents violin plots with embedded boxplots to exhibit the distribution and key descriptive statistics of datasets. The "All" plot, encapsulating 15-minute demand data from the facility monitored by ACU-MAIN, exhibits a broad distribution, as indicated by the expansive shape of the violin plot, suggesting substantial variability in the facility's total energy demand. The centrally situated boxplot within the violin plot delineates the median and interquartile range, providing a transparent comparison of demand dispersion against other circuit datasets.

Conversely, circuits 6 and 8 display a clustering of data around a narrow demand range, exhibiting limited variation and extremes, with circuit 8 also showing outliers. In contrast, circuits 10, 13, and 16, with wider violin plots and more pronounced boxplots, indicate a greater spread in demand and broader variability. Notably, circuit 12 is marked by a wide violin plot with an elongated boxplot and multiple outliers, alluding to a demand distribution with significant variation and extreme data points. For circuit 14, the scarcity of outliers suggests that extreme demands are either atypical or non-characteristic for this circuit. Upon closer inspection of circuit 14's violin plot, two distinct frequencies in energy demand are observed, implying that this circuit operated within two predominant demand ranges during the data collection period.

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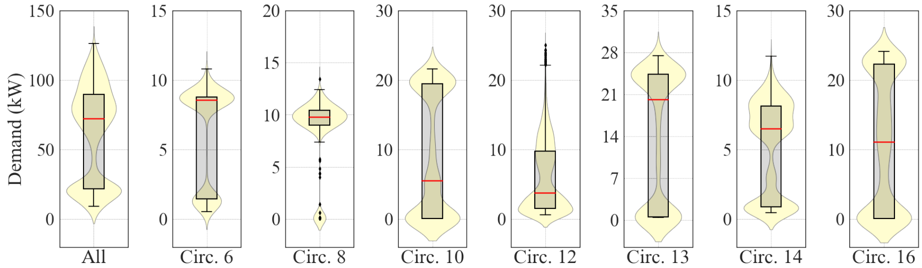

Fig. 5: 15-minute demand variation of the installation.

C. Preprocessing Input Data

The sliding window technique and min-max normalization were employed as preprocessing methods for the demand datasets of the main installation and circuits 6, 8, 10, 12, 13, 14, and 16. We leveraged the sliding window algorithm to prepare the model's input data, deriving it from sequential sample subsets, often termed sliding windows. These windows move forward based on a defined temporal unit, contingent upon the requirements of the application. Empirical evaluations suggested that a window size encapsulating 10 temporal units, where each unit corresponds to 15 minutes of prior demand data, proved effective in forecasting the energy demand for the imminent sample. We used a window of 150 minutes to forecast the subsequent 15-minute energy demand for each circuit of the installation.

Furthermore, the min-max normalization technique adjusts the dataset so that its values are confined within a predetermined range. This normalization is achieved by Equation (1). For this research's objectives, we designated the normalization boundaries as $[0, 1]$.

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

D. Evaluation Metrics

This section details the metrics employed to evaluate the performance of the TinyML models in demand forecasting.

1) Root Mean Squared Error (RMSE): This metric quantifies the discrepancy between the actual and forecasted values by computing the square root of the average of squared differences, as presented in Equation (2).

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}. \tag{2}$$

2) R-Squared Score (R^2): R^2 indicates how well the independent variables capture the variance in the dependent variable. A value nearing 1 suggests that the model closely fits the observed data, as depicted in Equation (3). Recent research suggests that R^2 is a more intuitively informative metric than RMSE for evaluating regression tasks [53].

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}. \tag{3}$$

E. Training, Validation and Test Subsets

We allocated 80% of the experimental data for training and reserved the remaining 20% for model validation. We then adopted the sliding window method to frame the input and output subsets during both training and validation phases. Again, our selected window size leveraged 150 minutes of past data to predict demand in the upcoming 15 minutes.

Owing to limitations in employee availability and the industry's readiness for ACU-BREAKERs and ACU-MAIN TinyML upgrades, these devices were removed in late April. Since they lacked FOTA capabilities in their earlier version, they were manually updated using serial communication. The ACUs were reinstalled on May 6, 2023. Throughout May to July, the embedded TinyML models in these devices monitored and predicted 15-minute demand intervals. Using these predictions, we validated the test outcomes, focusing on both the overall installation and the selected circuits.

F. LSTM Neural Networks

LSTM networks have demonstrated remarkable proficiency in the domain of time-series and sequential data analysis, surpassing many conventional AI models. This proficiency largely arises from the LSTM's inherent capability to establish temporal dependencies within data. LSTMs are designed with memory cells and can be architected with multiple layers, leading to stacked LSTM networks. Stacked networks offer an elevated level of temporal abstraction, enhancing accuracy in predicting sequential data, such as electrical demand forecasting.

Nevertheless, the computational complexity of LSTMs is substantially higher compared to many deep learning models. This makes deploying such networks on limited-resource devices challenging. This complexity can be evidenced in Equations (4)-(9) [54], detailing the underlying mathematical operation of the LSTM. This operation involves several variables: input gate (i_t), forget gate (f_t), output gate (o_t), candidate value ($\tilde{C}_t$), cell state (C_t), current hidden layer state (h_t), previous hidden layer state (h_{t-1}), in addition to the weight vectors W_i, W_f, W_o, W_c and their respective biases b_i, b_f, b_o, and b_c.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{4}$$

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{5}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{6}$$

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$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{7}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{8}$$

$$h_t = o_t \odot \tanh(C_t) \tag{9}$$

G. Quantization in Neural Networks

Quantization techniques aim to reduce model size to optimize memory usage during the inference stage of artificial neural networks on microcontroller systems. In this work, we will implement a process that involves truncating the precision of weights and activations by converting 32-bit floating-point values to 8-bit integers. This not only conserves memory but also reduces the microcontroller's processing load. However, a delicate balance between model precision and the precision of weights and activations is crucial. Overzealous reduction can degrade the neural network's performance [45].

The post-training quantization method is given by Equation (10), where x_{bit} is the new 8-bit integer value, x_{float} is the 32-bit floating-point value, C_s is an arbitrary floating-point scale coefficient, and C_z is an 8-bit integer offset value.

$$x_{bit} = \frac{x_{float}}{C_s} + C_z \tag{10}$$

H. Models Used for Forecasting

A comparison of learning models for energy demand forecasting was conducted in literature using the same datasets as this current research [20]. The comparative analysis included models such as Support Vector Regression, Random Forest Regression, XGBoost, and LSTM neural networks, with Linear Regression serving as the baseline. Notably, LSTM models excelled in terms of accuracy, although they required more time for inferences.

In this work, we extend our efforts to enhance the forecasting accuracy of LSTM models. Therefore, we explored variations of LSTM networks to achieve better performance. Keeping in mind that quantization could potentially reduce the prediction accuracy for each dataset, and the prior model had only one LSTM layer, we experimented with stacking LSTMs to enhance their learning capability and feature extraction. Figure 6 depicts the stacked LSTM architecture.

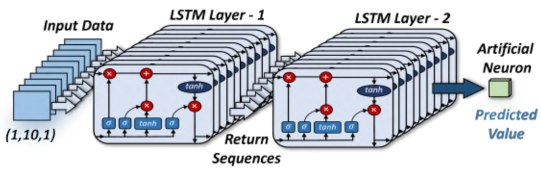

Fig. 6: Proposed stacked LSTM architecture.

The models were implemented using the Tensorflow 2.12.0 library in Python. Through the ESP-IDF framework, we deployed TensorFlow Lite Micro in C++ for predictions on the ESP32 of the ACUs, using ESP-NN optimizations. With the aid of the Bayesian optimizer, Optuna, we determined the optimal hyperparameters for the models relative to each dataset. Utilizing the Optuna framework, we conducted 100 trials to optimize each model for up to 100 epochs, implementing early stopping and employing the hyperbolic tangent (tanh) activation function in the LSTM layers. The choice of maximum epochs and trials was based on preliminary studies involving training on each dataset and the verification of model convergence.

VI. Results and Discussion

The evaluation conducted aligns with the single-layer LSTM network results from [20], utilizing the same dataset and time frame, from January 15 to April 12, 2023. For this purpose, we utilized a server matching the specifications in the cited work, a 2.3 GHz Intel Core i7-11800H processor with 16 GB RAM, 4 GB GPU, and a 500 GB SSD.

The methodology entailed training two-layer stacked LSTM models for each of the selected datasets, with a consistent sample window of 10 past 15-minute energy demand intervals for predicting future demand and a data division of 80 percent for training and 20 percent for validation. Subsequently, the models underwent quantization from 32-bit floating point to 8-bit integer to enable their deployment on the CPUs of retrofit platforms. It is noteworthy that the SoC ESP32, integral to the ACUs, operates at 240 MHz and includes 520 KB of SRAM and 4 MB of external FLASH memory.

The RMSE and R^2 metrics for the validation sets across each dataset are presented in Table IV. This evaluation employed 32-bit floating-point models on the server CPU and 8-bit integer models on the proposed ACUs. In the findings detailed in this table, the non-quantized stacked LSTM models developed in this research notably surpassed the performance of the single-layer LSTM models in [20] across the validation datasets. Moreover, the quantized stacked models showed improved performance on most validation datasets, except for circuits 12, 13, and 16, where their performance metrics did not surpass those of their non-quantized counterparts and single-layer models. In every instance, the RMSE performance mirrored the outcomes indicated by the R^2 metric.

In Table V, the performance metrics for the test datasets, which include 6,201 energy demand samples collected by each ACU from May 8 to July 11, 2023, reveal that non-quantized stacked LSTMs also excelled in the datasets for circuits 6, 8, 12, 14, 16, and the comprehensive "All" dataset, representing the 15-minute demand of the entire manufacturing facility.

TABLE IV: Performance metrics evaluated on selected demand validation sets from January 15 to April 12, 2023. RMSE is reported in kW, whereas R^2 is presented as percentage.

	LSTM 32-bit [20]		**Stack. LSTM 32-bit**		**Stack. LSTM 8-bit**	
Dataset	RMSE	R^2	RMSE	R^2	RMSE	R^2
All	8.22	94.07	8.01	94.36	8.17	94.14
Circ. 6	0.87	93.52	0.82	94.13	0.83	93.90
Circ. 8	0.42	87.39	0.41	87.68	0.41	87.56
Circ. 10	2.72	90.93	2.68	91.19	2.70	91.09
Circ. 12	1.29	94.30	1.28	94.38	1.38	93.46
Circ. 13	3.00	92.15	2.97	92.32	3.03	92.02
Circ. 14	0.58	96.47	0.56	96.68	0.58	96.49
Circ. 16	3.98	83.56	3.86	84.50	3.99	83.44

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TABLE V: Performance metrics evaluated on selected demand test sets from May 08 to July 11, 2023. RMSE is reported in kW, whereas R^2 is presented as percentage.

	LSTM 32-bit		Stack. LSTM 32-bit		Stack. LSTM 8-bit	
Dataset	RMSE	R^2	RMSE	R^2	RMSE	R^2
All	7.13	97.17	7.09	97.20	7.23	96.67
Circ. 6	1.04	95.16	0.98	95.72	0.98	95.74
Circ. 8	0.37	97.15	0.36	97.36	0.36	97.33
Circ. 10	2.13	94.93	2.22	94.50	2.26	94.32
Circ. 12	1.20	96.09	1.19	96.17	1.24	95.81
Circ. 13	2.42	94.05	2.47	93.82	2.54	93.48
Circ. 14	0.77	95.91	0.76	95.98	0.78	95.79
Circ. 16	2.70	93.81	2.64	94.10	2.83	93.22

In contrast, the quantized models showed a decline in performance compared to their non-quantized counterparts, attributable to the loss of precision during the quantization process. Nevertheless, the models' performance was similar in terms of RMSE and R^2, as evidenced by the results for the validation set in Table IV and the test set in Table V. Thus, if factors like seasonality, climate change, or variations in manufacturing output alter the predictions made by the ACUs, impacting the accuracy of these forecasts, FOTA updates can be employed to upgrade the firmware of the ACUs, along with the embedded prediction models in these sensor devices, aiming to improve model performance.

The stacked LSTM layers in the quantized models allowed them to retain a level of performance on par with the single-layer LSTM models. If deployed in a quantized form, this model might face additional precision losses in its predictions. Notably, the test dataset predictions were more accurate than those from the validation set, suggesting that the model's training on historical data, where previous seasonal variations could impact precision, has led to improved performance.

Figure 7 exhibits actual data with model predictions from June 30 to July 5, 2023. Despite being trained on earlier data, the models accurately mirrored these trends. The 32-bit stacked LSTM more closely aligns with actual data, showing superior accuracy and understanding of data complexity. In contrast, the 8-bit stacked LSTM, whereas following the general trend, shows deviations, especially in sharp data changes, indicating that its lower-bit representation might reduce predictive detail, suggesting a trade-off between computational efficiency and accuracy in capturing fine details.

Furthermore, Table VI provides a detailed analysis of the latency for single-sample prediction for each model within the test datasets, from data and model allocation to the final processed prediction. The latency can vary depending on the computational load on the server and the software services involved in data processing and sample prediction. Higher latency with more robust hardware may be influenced by factors such as the operating system and active services. As demonstrated, the latency was significantly lower for quantized stacked LSTM models, occurring in real-time on the developed retrofit platforms. It is noteworthy that increased model complexity leads to higher prediction latency, as evidenced by the non-quantized stacked LSTM model exhibiting greater latency compared to the single-layer model.

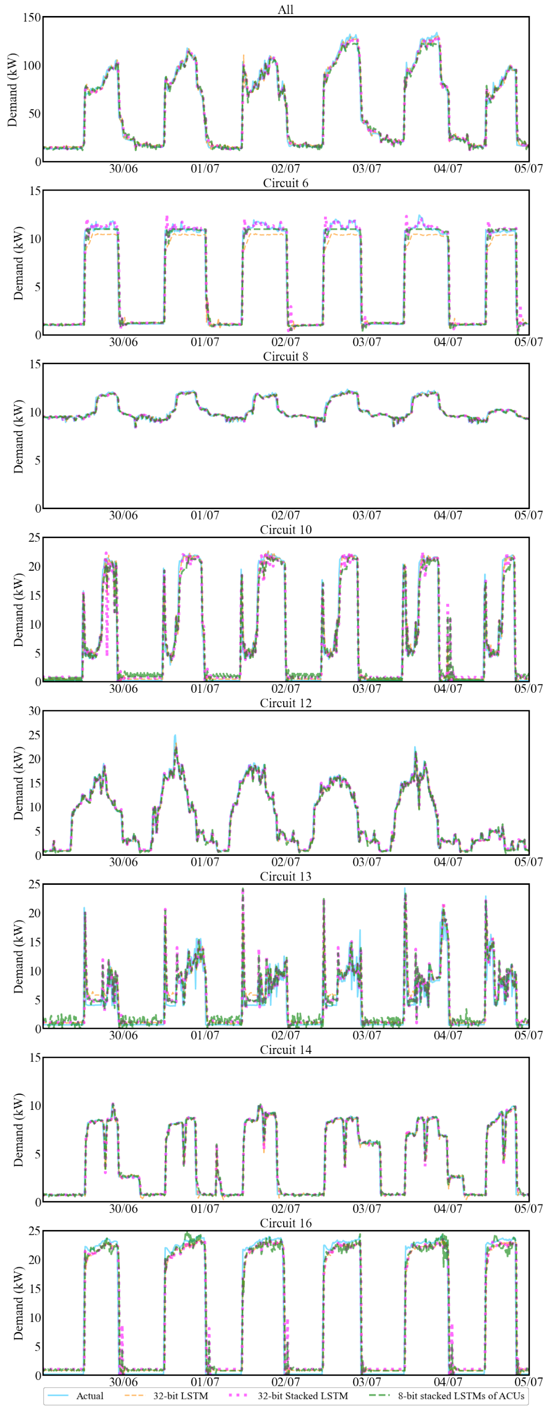

Fig. 7: Actual versus predicted demand from June 31 to July 5, 2023.

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TABLE VI: Latency of LSTM models.

Dataset	LSTM 32-bit	Stack. LSTM 32-bit	Stack. LSTM 8-bit
All	249.25 ms	429.33 ms	54.55 ms
Circ. 6	261.03 ms	415.78 ms	11.75 ms
Circ. 8	248.10 ms	405.11 ms	5.55 ms
Circ. 10	255.61 ms	419.17 ms	31.74 ms
Circ. 12	268.32 ms	417.16 ms	18.54 ms
Circ. 13	256.21 ms	411.54 ms	17.54 ms
Circ. 14	275.63 ms	435.37 ms	112.3 ms
Circ. 16	249.06 ms	430.30 ms	53.66 ms

The prediction latency may increase when utilizing cloud or fog computing, particularly in legacy facilities contexts lacking fast internet and robust network infrastructures. To address this, our study introduces a wireless sensor network employing ESP-NOW and MQTT protocols over Ethernet without internet communication. To evaluate the communication latency of our proposed network, we focused on measuring the Round-Trip Time (RTT) of data transmitted. Using ESP-NOW, the RTT for 18 Byte parameter requests sent from ACU-MAIN to ACU-BREAKERs and their 50 Byte responses were recorded. These packets included circuit energy demand, LSTM model predictions, and additional data specified in Table 1, yielding an average RTT of 4.79 ms. Further, latency between ACU-MAIN and the local server for transmitting comprehensive circuit data was assessed, averaging 57.47 milliseconds using MQTT over Ethernet with QoS 0. With the potential expansion of the system to include more ACU-BREAKERs, we anticipate an increase in total communication latency and data volume to the Supervision and Control Center (SCC). This necessitates the development of other interconnected sensing clusters to prevent network congestion at the system coordinator.

Following the integration of real-time offline capabilities into retrofit platforms, the computational workload previously managed by a local server has shifted to ACUs, leading to distributed computational expenses. This decentralization of the inference process to sensor nodes not only improves resource utilization but also enhances the overall responsiveness of the system. To quantify this distributed computational load, Table VII delineates the RAM and FLASH memory usage for energy demand inference via LSTM networks.

TABLE VII: Memory used for inference.

Dataset	LSTM 32-bit		Stack. LSTM 32-bit		Stack. LSTM 8-bit	
	RAM (KB)	FLASH (KB)	RAM (KB)	FLASH (KB)	RAM (KB)	FLASH (KB)
All	2.63	40.96	7.43	218.81	5.17	58.45
Circ. 6	2.16	25.96	4.01	57.54	4.95	17.27
Circ. 8	2.07	23.80	3.06	30.24	4.85	10.20
Circ. 10	3.95	120.38	5.20	137.64	5.05	37.73
Circ. 12	4.01	125.53	5.37	88.64	5.02	25.27
Circ. 13	2.95	54.87	4.97	85.12	4.99	24.35
Circ. 14	2.32	30.18	10.02	355.13	5.29	92.88
Circ. 16	4.57	177.56	7.56	211.91	5.16	56.67

The non-quantized stacked LSTM networks exhibited increased memory consumption compared to other architectures. Conversely, the single-layer LSTM network showed reduced RAM and FLASH memory usage for predictive inference tasks. However, for most datasets, the quantized LSTM models required considerable RAM usage, similar to the non-quantized models, but due to quantization, they consumed less FLASH memory than their non-quantized counterparts. Furthermore, they even used less FLASH memory than some single-layer models.

The proposed AIoT system, aligned with the SmartLVEnergy framework, revolutionizes legacy low-voltage circuits by integrating decentralized predictive capabilities through retrofit sensing platforms. These platforms are uniquely equipped with two-layer, 8-bit integer LSTM models, optimized for TinyML environments, offering a cost-effective solution for retrofit scenarios with limited microcontroller computational capacity. The ACU-MAIN platform, pivotal in monitoring and predicting main energy bus demand, doubles as a system coordinator, aggregating data from ACU-BREAKER units that monitor and forecast individual circuit demands.

This innovation significantly enhances edge computing functionalities, communication, and computational functionalities allocation for SCC. It allows for sophisticated modeling of the system, leading to the creation of retrofit platforms and communication protocols that embody the middleware and interoperability layers of the SmartLVEnergy metamodel. SmartLVGrid's operational primitives, DRFs, CSFs, and ISFs, are expertly crafted for decentralized predictive energy management, with DRFs tracking electrical parameters and energy demands in compliance with ANEEL regulations. The standout CSF is the system's short-term energy demand forecasting, which anticipates demand for each retrofitted circuit over the next 15 minutes, as per ANEEL standards. ISFs facilitate communication between ACU-BREAKERs and ACU-MAIN via the ESP-NOW protocol, and between ACU-MAIN and the local server using MQTT with QoS 0 over Ethernet.

For demand prediction, historical data from sensor devices in an existing factory setup was utilized. Eight demand datasets, including factory and individual circuit data, were selected to validate the AIoT system. Comparisons between existing single-layer LSTM models and our proposed two-layer stacked LSTM model, trained using similar preprocessing techniques and a 10-sample window for future demand prediction, highlighted the superior performance of our model. After quantizing these two-layer LSTM models from 32-bit float to 8-bit integer, they were implemented in the proposed ACUs. Performance comparisons of quantized and non-quantized stacked LSTM models, based on RMSE, R^2, memory usage and prediction latency, were conducted using both existing literature data and post-upgrade test data. The quantized models, while maintaining a precision comparable to other architectures, enabled faster on-device predictions than server-based forecasts at the SCC with a reduced and decentralized computational load. This approach redistributes processing costs from a centralized server to the retrofit platforms, marking a significant advancement in decentralized and intelligent energy management systems.

To conclude our analysis, we conducted a comparison between our approach and existing solutions, focusing on performance (Table VIII) and cost (Table IX).

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TABLE VIII: Benchmarking: Performance of different TinyML LSTM models in energy forecast scenarios.

Work	Model	TinyML Tool	Microcontroller Familly	CoreMark	No. of Features	Look-Back Period	Peformance Metrics	Model Size FLASH (KB)	Inference Time (ms)
[46]	2-Layer LSTM	TensorFlow Lite Micro	ESP32-S3	1181.6* (2 cores/240MHz)	7	2h (30-min ahead forecast)	R^2: 96.08 % RMSE: 0.0536 MW	∼22.26	∼4.83
[47]	Single-Layer LSTM	STM32 Cube.AI	STM32F3	245** (1 core/72MHz)	8	8h (1h-ahead forecast)	MAE: 0.048 kW	∼20.38	-
This Work (Circuit 8)	2-Layer LSTM	TensorFlow Lite Micro	ESP32	994.26*** (2 cores/240MHz)	1	1.5h (15-min ahead forecast)	R^2: 97.33 % RMSE: 0.358 kW	∼10.20	∼5.55

Data retrieved from: * [55], ** [56], *** [57].

Table VIII shows the top performance metrics for LSTM models in TinyML for predicting energy demand. Additionally, we used CoreMark to assess processing platform performance [58]. Given the different purposes, datasets, prediction horizons, and sample periods among this and previous studies, a comparison of existing LSTM models with this work in Table VIII cannot be assumed. Additionally, different studies employed distinct performance metrics. As in paper [46], we chose R^2 and RMSE to represent the performance of our model, with R^2 intuitively indicating energy demand prediction based on input parameters. Conversely, [47] provided MAE as the only performance metric, and the authors did not deploy the LSTM model on a microcontroller platform, as our work and [46] did. Our prediction had the shortest future time interval (15 minutes) and fewer input features. Moreover, our model used less memory due to fewer features compared to other TinyML LSTM models. Despite having a more complex model with more features, the ESP32-S3 with higher CoreMark than the ESP32 used in our hardware had significantly faster inference times, highlighting CoreMark's role in processor selection for TinyML applications.

Smart breakers are promising for upgrading electrical installations with wireless communication, ensuring interoperability with digital platforms, and providing real-time electrical data. Typically integrated into local Wi-Fi networks, they acquire unique IP addresses [59]. Nevertheless, as the number of devices directly connected to Wi-Fi networks increases without aggregator elements to manage Wi-Fi connections, network overload may arise, especially in legacy infrastructures less capable of handling increased traffic and IP addressing. Furthermore, replacing legacy breakers with smart ones raises sustainability concerns due to the disposal of usable breakers.

The retrofit approach can be refined to reduce impacts, aligning the installation effort with that of replacing circuit breakers. For integrating additional sensors or actuators through our framework, strategic analysis of PoIs can streamline efforts, allowing for the effective utilization of existing functional resources. Unlike existing market options, we tailored a solution for legacy infrastructure needs, preserving original breakers and adding predictive analysis for enhanced energy management. Our sensor solution attaches directly to existing breakers, integrating without discarding devices.

Table IX exhibits existing energy sensor solutions, highlighting their features and unit prices. It is important to note that the estimated pricing of our solutions is based solely on low-volume production costs, with competitor pricing sourced directly from manufacturer-associated references. Thus, it is not feasible to directly compare the final cost of our product with that of the manufacturers. In this case, the presented prices emphasize the competitiveness of our solution. In high-volume production, where unit costs typically decrease, our pricing could become even more advantageous. Additionally, while our solution lacks some communication features found in other products, it uniquely incorporates predictive resources in its sensor elements for energy management.

TABLE IX: Benchmarking: Cost-benefit.

Product	Function	Commun. Standards	Real-time Sensing	Predictive Resources	Unit Price (EUR)
[60]	Sensor	IEEE 802.15.4	[X]		164.50
[61]	Data Gateway for [a]	Modbus IEEE: 802.3 802.11 802.15.4			446.00
[62]	Smart Breaker	LTE* IEEE: 802.11 802.15.4	[X]		89.00**
ACU-MAIN	Sensor/ Data Aggregator	IEEE 802.11	[X]	[X]	38.61
ACU-BREAKER	Sensor	IEEE 802.11	[X]	[X]	21.43

*: Abbreviation for Long-Term Evolution.
**: Price retrieved from: [63].

VII. Conclusion and Future Work

This paper proposes the SmartLVEnergy framework, a novel approach to enhance energy management in legacy systems through the combined power of predictive sensing and decentralized computation. Building upon the foundation of the SmartLVGrid metamodel, SmartLVEnergy leverages Cloud, Fog, and Edge computing technologies to facilitate the implementation of AIoT-based retrofit solutions. As demonstrated in a practical application, SmartLVEnergy successfully established a system capable of monitoring and forecasting short-term energy demand directly on sensor devices within a legacy industrial distribution panel. This system utilized quantized Long Short-Term Memory (LSTM) networks within the TinyML framework, achieving a critical balance between computational efficiency across retrofit solutions and minimized latency. This optimization enabled real-time operational decision-making, ultimately leading to improved energy management within legacy low-voltage consumer units through the integration of predictive and monitoring capabilities.

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Future work could explore:

- Decentralized control solutions through SmartLVEnergy.
- Comprehensive economic feasibility analysis of SmartLVEnergy implementations.
- Transfer learning strategies to avoid training specific models for each circuit.
- Evaluating framework performance in different systems and integrating cloud and fog computing solutions.
- Assessing the economic impact and integration of these energy management systems with sustainable energy generation and dynamic energy markets.

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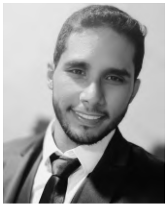

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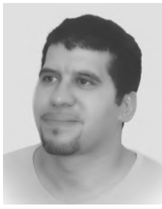

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4 CONCLUSÕES

Esta tese propõe o *framework* SmartLVEnergy, concebido para modelar estratégias sistemáticas de *retrofit* para modernizar e desenvolver ferramentas de gestão energética em unidades consumidoras pré-existentes, utilizando soluções de Internet das Coisas (IoT) e de Inteligência Artificial das Coisas (AIoT). Nas experimentações apresentadas, isso possibilitou a elaboração de estratégias para monitoramento remoto, análises preditivas e distribuição descentralizada dos recursos computacionais, viabilizando a implementação e desenvolvimento de tecnologias avançadas em infraestruturas legadas de baixa tensão.

As estratégias propostas incluíram, sistematicamente, recursos de sensoriamento em tempo real, utilizando *middlewares* cuidadosamente modelados com interfaces físicas e lógicas bem estabelecidas e ajustadas às necessidades dos sistemas pré-existentes. Isso permitiu o uso eficiente desses recursos para a convergência tecnológica e virtualização de sistemas energéticos prediais e industriais legados. Com isso, as experimentações realizadas promoveram a interoperabilidade e interconexão dos dispositivos de monitoramento em redes de dados sem fio, adaptadas às necessidades das instalações existentes. É importante mencionar que os recursos de *middleware* e de interoperabilidade propostos, fundamentados nas pilhas de protocolos do metamodelo SmartLVGrid, maximizaram a utilização e preservação dos recursos presentes na infraestrutura das unidades consumidoras legadas.

Mostrou-se também a distribuição e descentralização de recursos computacionais em borda, nuvem e localmente, para visualização, armazenamento e processamento dos dados energéticos adquiridos, conforme as necessidades específicas das instalações. Isso atribuiu às unidades consumidoras pré-existentes a capacidade descentralizada de utilização dos recursos computacionais especializados para a gestão energética dessas instalações. Isso também envolveu a coleta e construção de bases de dados das unidades consumidoras legadas e seus respectivos circuitos, que geralmente não possuem bases de dados existentes ou recursos para análise avançada dos parâmetros monitorados.

Utilizando os dados adquiridos ao longo da pesquisa, foi possível analisar a demanda energética e outros parâmetros das instalações, em conformidade com as regulamentações da ANEEL. Isso permitiu a otimização e o planejamento dos recursos energéticos de acordo com as necessidades específicas das instalações. Também foi possível incluir recursos preditivos para demanda energética, com o intuito de auxiliar as unidades consumidoras em análise no controle desse parâmetro, para detectar possíveis ultrapassagens de demanda que pudessem aumentar a oneração energética dessas instalações, conforme as regulamentações do setor elétrico brasileiro. Isso foi implementado tanto a nível centralizado quanto distribuído nos próprios elementos sensores (*middlewares*) desenvolvidos, através das técnicas de TinyML incluídas graças aos recursos propostos pelo *framework* SmartLVEnergy.

Neste contexto, conclui-se que o *framework* SmartLVEnergy, ao generalizar estratégias de modernização com soluções IoT e AIoT, contribui significativamente para o avanço da atualização tecnológica rumo à gestão energética eficiente de unidades consumidoras legadas de baixa tensão. As estratégias de *retrofit* baseadas no *framework* não apenas promovem a preservação e otimização dos sistemas existentes, mas também se destacam como soluções sustentáveis, potencializando a gestão energética por meio de uma evolução tecnológica gradual e efetiva. Além disso, essa abordagem garante a escalabilidade das soluções tecnológicas para o setor elétrico de baixa tensão, adaptando-se a diferentes cenários e sistemas. Isso é possível graças às interfaces físicas e lógicas, além dos recursos computacionais distribuídos e descentralizados integrados às infraestruturas existentes, conforme suas necessidades, baseadas na estrutura do SmartLVEnergy. O *framework* proposto abraça a flexibilidade, expansibilidade e interoperabilidade ao longo de toda a instalação, permitindo operações conforme as peculiaridades e recursos de cada contexto. Esta versatilidade confirma a relevância deste trabalho como uma proposta robusta para os complexos desafios energéticos da atualidade, especialmente em unidades consumidoras pré-existentes.

4.1 DESAFIOS DE PESQUISA E TRABALHOS FUTUROS

Como principais desafios de pesquisa e trabalhos futuros, destaca-se a necessidade de estudos prévios especializados para definir os recursos a serem utilizados nas estratégias de modernização em cada caso, pois as particularidades das infraestruturas podem variar significativamente. Embora o *framework* SmartLVEnergy possa fundamentar e orientar as ações a serem tomadas, tecnologias de automatização, de comunicação ou computacionais mais avançadas podem ser difíceis de implementar nesses ecossistemas devido ao grau de precariedade das instalações e aos recursos limitados para investimento no processo de transformação tecnológica. A ausência de dados sobre essas infraestruturas é outro fator que retarda o processo de modernização, necessitando de recursos mínimos para viabilizar análises energéticas avançadas. Para isso, o *framework* pode orientar a alocação de recursos físicos e lógicos para viabilizar essa transição com mínimos impactos e investimentos. Ainda, estudos futuros podem contribuir para determinar quando a abordagem do *retrofit*, por meio dos protocolos do *framework* SmartLVEnergy, torna-se viável ou não economicamente para ser utilizada na modernização de ambientes pré-existentes.

O SmartLVEnergy pode ser a chave para a integração de recursos digitais e de Inteligência Artificial em infraestruturas existentes rumo aos paradigmas "*Smart*", como os paradigmas de *Smart Buildings*, *Smart Cities*, *Smart Industries*, *Smart Homes*, Indústria 4.0/5.0, entre outros, no que tange aplicações para o domínio energético. No entanto, seus conceitos e premissas podem se estender para outros ecossistemas no domínio destes paradigmas, incluindo monitoramento ambiental, de recursos hídricos, entre outros, contribuindo para aprimorar recursos tecnológicos defasados com tecnologias emergentes, de forma gradual e com mínimos impactos socioeconômicos.

Outro aspecto que deve ser explorado envolve alternativas ao treinamento individualizado dos modelos para cada circuito das unidades consumidoras em análise, que se mostrou uma tarefa dispendiosa nos trabalhos publicados, computacionalmente e analiticamente. Trabalhos futuros podem abordar o uso de aprendizado federado voltado ao setor elétrico através do próprio SmartLVEnergy, para contemplar funcionalidades computacionais em borda para viabilizar o treinamento dos modelos nas próprias plataformas de *retrofit*. Nesse contexto, a segurança dos dados analisados é outro aspecto que deve ser discutido futuramente para preservação das informações obtidas das unidades consumidoras, com análises mais profundas dos recursos computacionais de segurança utilizados na concepção das soluções propostas para o gerenciamento energético associado a tecnologias digitais.

Um desafio de pesquisa no âmbito desta tese foi a impossibilidade de implantação das estratégias experimentais e práticas envolvendo técnicas de acionamento e controle nas instalações em estudo, devido a restrições relativas às próprias regras de negócio das unidades consumidoras em análise. Pretende-se que trabalhos futuros possam incluir a utilização de elementos de atuação para viabilizar o controle energético automatizado em infraestruturas legadas. Além disso, devido à ausência de fontes alternativas de geração renovável ou não renovável nestas unidades consumidoras, não foi possível integrar as soluções projetadas para o gerenciamento automatizado junto a essas fontes alternativas. Outros trabalhos podem promover essa integração, considerando um gerenciamento econômico mais aprofundado com a participação em mercados dinâmicos de energia para uma gestão energética mais eficiente, permitindo a compensação da demanda e do consumo energético com outras fontes energéticas na instalação junto à concessionária de energia conforme o custo-benefício.

Ressalta-se que o *framework* SmartLVEnergy não contempla em sua concepção recursos para embasar processos sistemáticos de modernização de sistemas de média e alta tensão no setor elétrico. A criticidade de operações de modernização de infraestruturas de média e alta tensão pode contemplar complexos desafios de sensoriamento, controle, comunicação e processamento de dados que podem ser explorados em trabalhos futuros, com o intuito de expandir a aplicabilidade do *framework* proposto rumo à digitalização de redes elétricas mais complexas e abrangentes.

A impossibilidade de expandir as estratégias propostas devido ao número reduzido de quadros de distribuição das unidades consumidoras analisadas foi outra limitação de pesquisa no âmbito desta tese. Trabalhos futuros podem avaliar a usabilidade do *framework* em cenários legados mais extensos e complexos. Neste trabalho, a estratégia de *retrofit* consistiu unicamente no *retrofit* dos disjuntores dos quadros de distribuição em análise. Outras verificações que promovam o aproveitamento máximo e viabilizem o *retrofit* de outras formas também são aspectos a serem explorados em outras propostas. Além disso, os artigos que compõem esta tese abordaram principalmente a demanda energética, mas o consumo e outros parâmetros voltados para a qualidade de energia também poderão ser explorados futuramente para uma análise energética mais aprofundada, operando de forma conjunta com soluções digitais para viabilizar a atuação sobre o controle energético, de forma a garantir a qualidade do serviço e melhores resultados em termos de impactos econômicos.

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APÊNDICE A . PRODUÇÕES PUBLICADAS EM CONFERÊNCIAS

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- Fernandes, R. A.; Seppe, F. R.; Júnior, C. T. C.; Torné, I. G.; Filho, C. D. S.; Rego, S. B. T. A Bayesian Optimization Approach of Ensemble and Decision Tree Learning Applied to Industrial Energy Consumption Prediction. 2023 IEEE INTERNATIONAL CONFERENCE ON INDUSTRY APPLICATIONS, São Bernardo do Campo, 2023. p. 842-849. DOI: 10.1109/INDUSCON58041.2023.10374661.