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A PRIVACY-PRESERVING EDGE DATA AGGREGATION FOR TINYML ENERGY FORECASTING IN HOUSEHOLDS

The object of this research is the use of tiny machine learning (ML) forecasting models and low-power edge processing as a part of a hybrid energy management system (HEMS) with a particular emphasis on ensuring end-user data privacy and trust. The research addresses the challenge of the collection, aggregation, and processing of sensitive data in smart grid operational modes decision-making tasks.

An in-depth literature review revealed that failing to meet user expectations for control and privacy often leads to dissatisfaction and disengagement. This study introduced a complex solution that tries to solve the indicated gap and proposes a prototype of a HEMS data aggregation subsystem designed to supply information to an energy consumption forecasting module based on mobile ML models.

The developed LSTM-based household energy consumption forecasting models were converted into CoreML and TensorFlow Lite formats, maintained accuracy with an RMSE of 0.211 kWh, inference time under 0.5 ms, 800 kB size on disk, and up to 20 MB RAM usage. These results confirm their feasibility for deployment in HEMS forecasting subsystems on low-power edge devices.

To supply these models with data, a prototype of the HEMS data aggregation system was developed. It uses open-source software (Home Assistant, InfluxDB) and a scalable, privacy-centered container architecture that keeps sensitive data at the edge. Tests on Raspberry Pi 5 (16 GB) showed 97.2% availability over 72 hours, with 12% RAM usage, 18% CPU load, and CPU temperatures of 44–51°C when processing 1440 records per sensor daily. This confirms reliable aggregation with low resource demands and good scalability.

Considering the results, the models and prototype can be considered as the sensing and edge computing layers of HEMS, providing the necessary data for operational mode selection in household microgrids.

Keywords: *energy management systems, energy efficiency, Internet of Things, smart grid.*

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1. Introduction

Rising energy prices and growing demand are driving the development of smart strategies for monitoring, controlling and saving energy. Demand side management is an important approach to preventing major supply problems and improving energy efficiency [1]. Hybrid energy management systems (HEMS) are an important part of demand side management. These systems reduce costs while meeting all energy needs. They analyze how consumers use energy and adjust operations using energy-saving algorithms. HEMS integrate different energy sources, such as heat pumps, solar panels and the standard electricity grid. They work together to deliver heating, electricity and hot water in the most efficient way.

HEMS aims to save money and operate efficiently by using less energy and maintaining a consistent level of comfort. The system collects real-time energy consumption data, processes it, and determines the appropriate response when conditions change. HEMS uses Internet of Things (IoT) technology to improve productivity and reduce energy waste [2]. IoT connects devices, systems, and services so that they can instantly exchange data and automate operations. The energy supply process involves many parties with complex relationships. These interacting parties include consumers, IoT systems, and utilities [3]. These relationships are governed by established quality of service standards and system constraints that control their cooperation.

Consumers are the end users of utility services provided through IoT systems. For them, the top priority is "Quality of Use". This includes satisfaction, low risk, and Users' Experience (UX). The quality aspect is extremely important because it directly affects the consumer's perception of and trust in IoT services. The degree of satisfaction is determined by how well the IoT system meets expectations. To achieve a high level of satisfaction, easy-to-use interfaces, reliable help, and quick client assistance are necessary [4].

HEMS is an IoT system built on five layers, including both cloud and edge computing [5]. It acts as a point of contact between consumers and utilities. The most important quality metrics for IoT systems are reliability and availability. The reliability of a system depends on two factors: the ability to operate stably over a long period of time and resistant to failures. Reliable systems provide continuous monitoring and control of services, minimizing downtime and failures. Availability is defined as the degree to which an IoT system is operational and available when needed. High availability is critical for real-time data processing and immediate response to consumer needs.

Utility companies provide services but must operate within certain limits. These limits fall into architectural and regulatory limits [6]. Architectural limits are the technical boundaries that a system must adhere to. These limits cover how well a system can evolve (scalability), whether it works with other systems (integration), and if IoT devices fit existing infrastructure (compatibility). Regulatory limits are the government

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rules and industry standards that utility companies must obey. These rules ensure that services are safe, fair, and available to everyone. They also define standards for data processing, protecting consumers, and effects on the environment. Adherence to these constraints and quality standards, as well as maintaining consumer confidence in HEMS, is critical for the proper operation of the systems. Previous research has mostly addressed architectural and regulatory issues but didn't pay sufficient attention to trust and privacy from the user perspective.

Machine learning (ML) models for predicting energy demand in HEMS are still being actively studied. However, most research focuses on cloud-based predictions and ignores the deployment of ML models on edge devices. Modern smartphones can run complex ML models directly on the device without sending personal data anywhere else. Incorporating these personal devices into HEMS designs can increase user trust in the system.

Thus, *the object of this research* is the use of mobile ML forecasting models and low-power edge computations as a part of HEMS with focus on end-user data privacy and trust. *The aim of this research* is to evaluate the potential of privacy-preserving edge computing solutions to improve HEMS trustworthiness.

To achieve the stated aim, the following research objectives were defined:

1. Identify and analyze the key factors influencing the trustworthiness of hybrid energy management systems (HEMS) from the end-user perspective.
2. Develop, optimize, convert and evaluate LSTM-based short-term household energy consumption forecasting model for deployment on smartphones.
3. Design, implement and evaluate a privacy-preserving energy consumption data aggregation and forecasting support prototype for home-based HEMS using edge computing on low-power edge devices.

2. Materials and Methods

This study uses a mixed-method approach to explore the integration of edge computing via smartphones into HEMS for microgrids. The focus is on balancing data privacy and performance from the end user's perspective. The methodology uses a combination of qualitative and quantitative methods. Firstly, a literature review was conducted to summarize knowledge on system trust, energy forecasting and edge computing. As the second step, ML models were built, converted and tested to evaluate their predictions accuracy and stability for running on low-power edge devices. Finally, a prototype had been developed to evaluate real world scenarios for privacy aware data aggregation and processing on the close edge of a smart grid to reduce the risks of data leakage. The prototype development was done with data protection legislation in mind, such as the GDPR. The proposed solution is designed to keep and process users' data locally without dependency on cloud computations.

The literature review looked at peer-reviewed sources from IEEE Xplore, Scopus, and Google Scholar databases. Keywords such as "HEMS reliability", "edge computing in microgrids", "LSTM energy forecasting", and "privacy in IoT energy systems" were used for searching relevant open-access sources and publications over the last decade. Over 50 articles were reviewed, and 20 were selected for detailed analysis based on their relevance to stakeholder experience, system limitations, and reliability metrics. This allowed to identify gaps in current research. In particular, there is a lack of user-centric privacy assessments in HEMS. To address these identified gaps, particularly in privacy-preserving prediction and secure training data collection, the study is continuing to develop ML models adapted for deployment on smartphones, and tools for secure data collection, ensuring compliance with user preferences for data sharing.

Electricity consumers have unique consumption profiles but can be broadly categorized into three groups: households, social infrastructure facilities, and industrial enterprises. LSTM-based models have proven their efficiency in short-term energy consumption forecasting tasks for all these groups [7]. In the previous work, mobile short-term forecasting models for social infrastructure facilities and industrial enterprises were developed and evaluated [8]. The present study extends this line of research by addressing the household category, thereby filling an identified gap in forecasting model development.

TensorFlow Keras was chosen as the ML backend to develop a test LSTM model. It allows fast model prototyping and is compatible with various ML model conversion tools. To be launched on iOS devices (Apple Inc., USA), ML models require conversion to compatible mobile formats, like TensorFlow Lite (Google Brain Team, USA) and CoreML (Apple Inc., USA). This conversion can be done using TensorFlow Lite and CoreMLTools (Apple Inc., USA) frameworks accordingly. TensorFlow and CoreML platforms allow development and deployment of LSTM-based forecasting models on mobile and low-power devices (TinyML approach [9]) with efficient execution on CPUs, GPUs, and neural processing units (NPUs). These platforms are compatible with the majority of modern smartphones and enable edge-level forecasting without dependency on the cloud infrastructure. Although CoreML supports on-device fine-tuning for certain ML models, LSTMs currently lack this functionality [10] and Tensorflow Lite is not officially supporting on-device training for iOS [11], so retraining must be performed on a dedicated edge hub or via cloud services.

The conversion process includes models' optimizations and ML operators' adaptation that may impact model performance, so it should be re-evaluated after conversion. The RMSE value of forecasting results can be used to evaluate ML model degradation. Also, it is crucial to validate that a low-power device like a smartphone meets the forecasting model computational power requirements and can guarantee its stable work. This aspect can be validated by measuring device CPU utilization, RAM consumption, thermal state changes, ML model disk space size, and inference speed. It was decided to run such tests three times per configuration to achieve the statistical reliability (e. g., via *t*-tests for significance). Detailed methodology of evaluation of these values was described in the previous work [8].

To enable training AI models on user data, it is necessary to have a tool that implements secure collection of energy consumption data with the possibility of further transmission to the forecasting subsystem. Edge computations allow local collection and storage of such data without the use of cloud services. When users have full control over their sensitive data, it may improve their trust in the HEMS system. In addition, it is important that the data collection and aggregation tool is compatible with a large number of smart grid devices and does not require significant investments for deployment.

To test the feasibility of this idea, it was decided to develop a prototype using Home Assistant (HA) (Nabu Casa, Inc., USA) [12] as a core component. It is an open-source software package, which is compatible with a majority of IoT devices out of the box and has custom plugins that support integration of almost any smart meter and inverter. HA can be deployed on a low-power computing hub. It is commonly used as a main integration point for different IoT-based systems, including smart homes and smart energy monitoring [13, 14].

InfluxDB (InfluxData Inc., USA) [15] was selected as the main data storage for the prototype. It is specifically designed to handle large amounts of time-series data. HA has its own built-in storage, but its functionality and capacity are limited. In addition, the access to the data is only available with an admin access token, which is not secure. InfluxDB storage is local and users have full control over their data, which significantly improves their trust to the system.

To be able to integrate with other subsystems, the prototype should have an authorized API for secure data access. FastAPI (Sebastian Ramirez, USA) [16] framework for Python (Python Software Foundation, USA) allows quick and secure API development that suits the prototyping task well. Caddy (Light Code Lab LLC, USA) [17] can be used as a web server, as it allows quick hosting of the API with a sufficient level of security. To make the prototype modular and easier to deploy, it was decided to use Docker and Docker Compose (Docker Inc., USA) [18].

Telegraph (InfluxData Inc., USA) with InfluxDB integration [19] can be used for the prototype telemetry collection as it has a wide list of metrics that can be tracked, like CPU, RAM usage, etc.

To host the mobile forecasting model and test the integration with the prototype, the iOS application from the previous research [8] can be used as a template for the companion application implementation. The application should be modified to be able to read data from the prototype API and use the forecasting model described in this paper. The application will be built using Swift and SwiftUI (Apple Inc., USA) as the main programming language and UI framework accordingly.

Raspberry Pi 5 [20] 16 Gb is a low-power edge computation device that supports all required tools for the prototype development and testing, so it was chosen as the edge computations hub. In addition, it is commonly used as a central hub in smart homes and it will be easier to find potential candidates for the closed beta testing in the future.

For the prototype testing it will be hosted in a household with 3 Shelly Plu Plug S (Allterco Robotics (Shelly), Bulgaria) [21] that track energy consumption in three different rooms once per minute. To confirm the feasibility of the prototype, these parameters will be tracked during 72 hours: system availability, collected sensors data volume per day, system load (including CPU load, RAM usage, device thermal state) using Telegraph. In addition, the total InfluxDB buckets size will be measured after 1 month of active sensors data tracking.

Developing short-term energy consumption models faces several challenges. First, getting data is difficult because users don't want to share it due to privacy concerns. Second, users want to use ML models that don't send their data to outside servers. This work aims to create short-term energy consumption models that accurately predict energy use on personal devices. Smartphones can serve this purpose by using consumption data that's collected on the edge and processed locally on the device.

To meet the research goals, the proposed methodology was applied, and its efficiency was evaluated using empirical results, as shown below.

3. Results and Discussion

3.1. Assessing trustworthiness in HEMS

To address the first objective of this paper, the trustworthiness of HEMS should be assessed across several dimensions [22–24]. These include technical performance [25–27], economic viability [28, 29], sustainability impact, and privacy-preserving mechanisms [30, 31].

Technical performance:

– *Reliability.* The system must consistently manage energy distribution and consumption without failures.

– *Availability.* The system must always remain operational and accessible when required.

– *Controllability.* The system must be able to adapt its consumption models based on both user preferences and external conditions [32].

– *Feedback/Monitoring.* The system provides real-time data on consumption, peak usage and offers suggestions for optimization [33].

– *Usability.* This requires intuitive interfaces and remote operation (via mobile or voice) to ensure user satisfaction [34].

Economic performance:

– *Energy savings.* Reduced energy consumption while maintaining comfort [35].

– *Cost-effectiveness.* Achieving long-term savings that justify the initial investment.

– *Low maintenance.* Requiring minimal upkeep and exhibiting reduced failure rates.

– *Environmental benefits.* Contributing to reduced carbon emissions and meeting sustainability goals.

Privacy-preserving performance:

– *Security.* The strong protection against illegal access, including encryption and secure data transfer.

– *Privacy.* Anonymous use of data with user consent, ensuring compliance with regulations and maintaining trust.

The UX of the end-user strongly affects trustworthiness. Studies show that when system design does not match user expectations, it often leads to dissatisfaction or even increased energy use [29]. Privacy concerns also act as barriers, as users resist loss of autonomy, choice, and control [36]. At the same time, users are more willing to share data when benefits are transparent, predictable, and mutually advantageous [37, 38]. Research suggests data-sharing willingness typically lasts about one month, with repeated transparent requests improving acceptance, like in case with smartphones sensors data sharing requests [39], though this period is insufficient to train forecasting models with seasonal accuracy if applied to the energy data sharing problem. User-controlled data storage and model fine-tuning can therefore enhance trustworthiness. Additionally, some users prefer to limit remote control of appliances or heating schedules, as full automation may be perceived as a loss of control [40].

To effectively optimize energy use, modern HEMS must adapt strategies to the UX. A key method for determining these needs is artificial intelligence-based energy consumption forecasting, which requires sensitive historical data on consumption for training. Because of these, there are privacy concerns. Therefore, it is important to think carefully about the modelling approach, the size of the dataset, and the whole structure of the HEMS. It allows data to be processed locally on low-power devices. Therefore, a balance between prediction accuracy and privacy is achieved thanks to limited data storage and the absence of third-party involvement. However, a model transformation may result in performance trade-offs.

To explore these assumptions and support trustworthy HEMS with accurate, privacy-respecting predictions, this study evaluates forecasting models on datasets representing key consumer categories. The optimized and converted models constitute the predictive core of the proposed HEMS prototype, which integrates edge computing to enable local forecasting and automation. Summarizing the literature, general indicators that ensure trustworthiness from the UX perspective in HEMS are identified and illustrated in Fig. 1, where the most influential factors are highlighted.

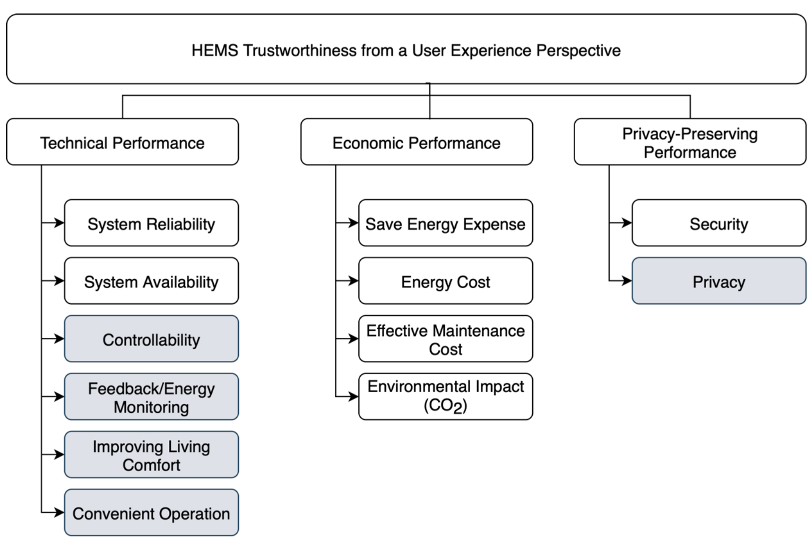

Fig. 1. Factors influencing trustworthiness in HEMS

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3.2. LSTM forecasting model development, conversion and evaluation

This section addresses the second task of the paper.

The household dataset was collected from a private residence in Sumy, Ukraine, spanning 9 months of hourly electricity consumption data, supplemented by microgrid parameters (e. g., solar generation, battery levels, grid imports/exports). Only consumption and timestamp data were used for training, with 0.26% missing or anomalous values interpolated linearly using Pandas (Wes McKinney, USA). The dataset visualization is presented in Fig. 2. The average hourly consumption ranged from 0.3–0.8 kWh (Fig. 3), exhibiting a right-skewed distribution (median ~0.4 kWh) with outliers due to usage peaks, as shown in the histogram (Fig. 4, *a*) and boxplot (Fig. 4, *b*). LSTM forecasting models were trained using TensorFlow Keras (input 24 × 1, LSTM 200, Dense 100, Dropout 0.2, output Dense 1) with batch size 16, 20 epochs, Adam optimizer, and MSE loss function. Consumption history data was scaled with MinMax scaler and validated using the walk-forward approach. The dataset was split on 75% train and 25% test data. Models were converted to CoreML, TensorFlow Lite with SelectTfOps enabled, Float32 precision.

The household model achieved RMSE 0.211 kWh for energy consumption predictions. After conversion, the RMSE value didn't change, that means there is no prediction accuracy loss for both formats. CoreML showed slightly faster inference (0.2–0.3 ms vs. 0.4–0.5 ms). During predictions, both CoreML and Tensorflow Lite models caused short CPU load spikes without thermal impact; each required up to 20 MB RAM and ~800 kB of disk space. Predictions reflected weekly consumption patterns correctly (Fig. 5).

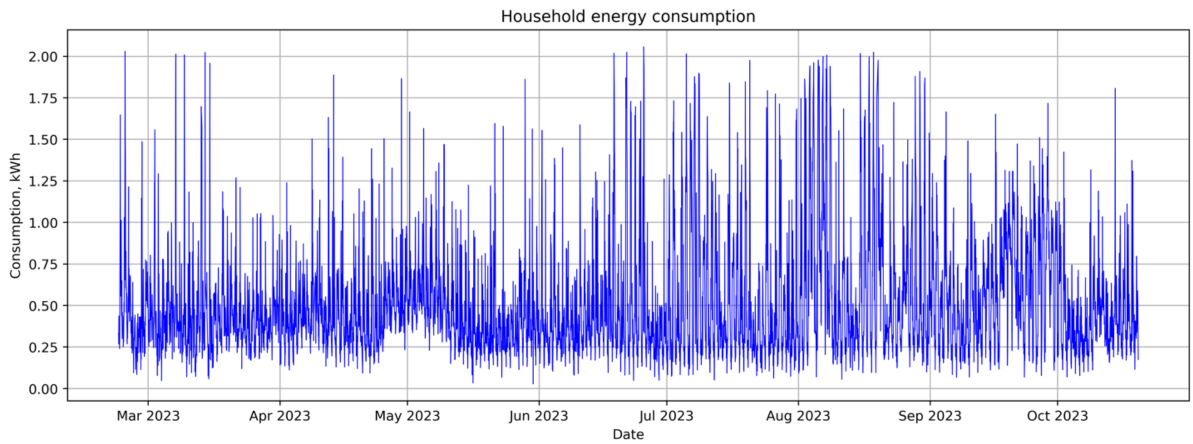


Fig. 2. Household consumption data visualization

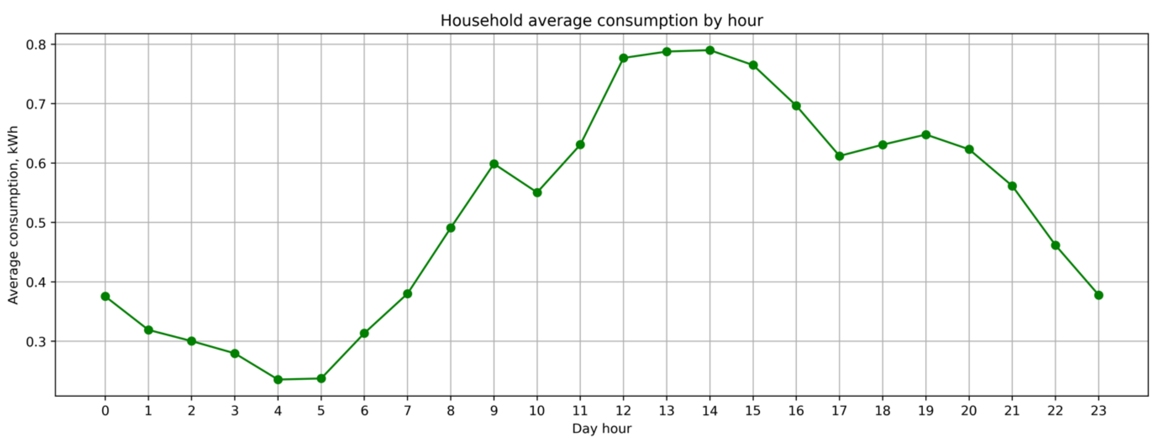
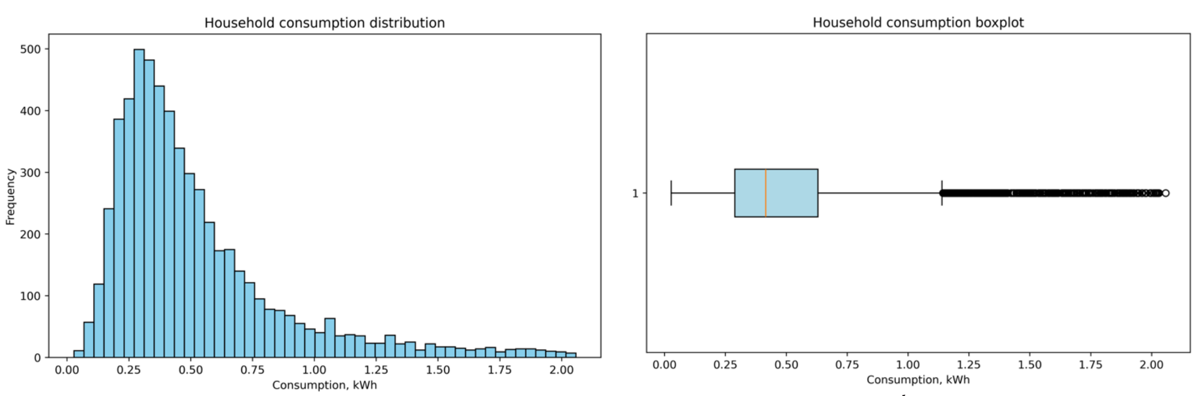


Fig. 3. Household hourly average consumption



a *b*

Fig. 4. Household consumption data: *a* – consumption distribution histogram; *b* – consumption distribution boxplot

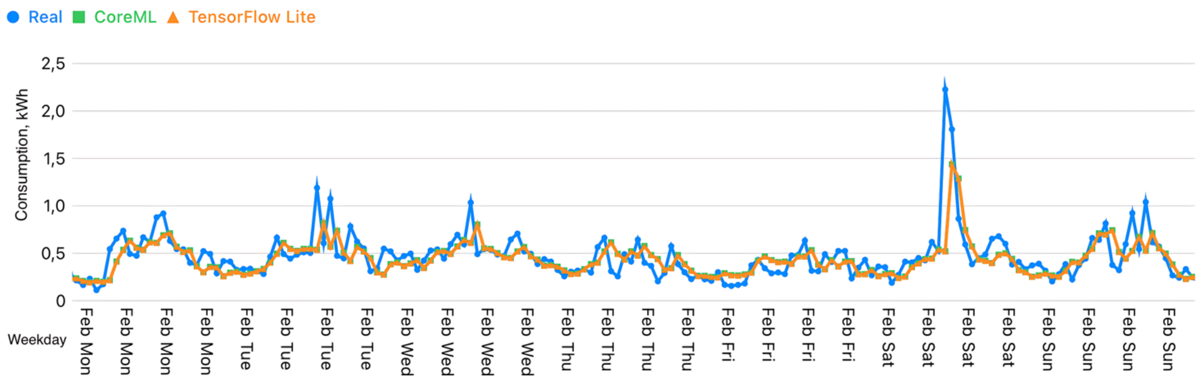


Fig. 5. Example of predicted and actual consumption indicators from the household dataset. Scale: 1 week

These results confirm that LSTM-based mobile models can provide real-time forecasts with acceptable precision on non-flagship iOS devices as part of a HEMS prediction subsystem for households.

After validation the mobile consumption prediction model for households, the next step was its real-world application. It was decided to begin with the development of a data aggregation subsystem to provide the necessary inputs for the prediction module.

3.3. Prototype implementation

To address the final task of this paper, a privacy-focused HEMS data aggregation subsystem prototype was developed as an edge computation hub hosted on a Raspberry Pi 5 16 Gb.

Key components of the prototype include:

– *Data Aggregation:* Home Assistant (version 2024.8) serves as the core integrator, tracks connected sensors state changes in real-time and passes it to the local storage, enabling granular monitoring without cloud dependencies.

– *Storage:* InfluxDB (version 2.7) is used as the main data storage of the prototype. Contains 2 data buckets – raw data bucket and hourly data bucket.

– *Data access and security:* Caddy web server runs API that provides read-only access to the hourly consumption data from InfluxDB. The API uses JWT-based authentication, self-signed HTTPS certificates, encrypted tokens storage and role-based access control (RBAC) to provide only secure authorized access to the data. Additionally, network layer of the subsystem is protected with firewall rules (ufw).

– *Deployment:* the subsystem is containerized in two Docker images: HA with InfluxDB, and API. Resource allocation allows to limit CPU and memory usage per container to prevent overload on the Raspberry Pi.

– *Forecasting subsystem integration:* the developed companion iOS mobile application pulls aggregated data via API and makes on-device predictions using mobile ML models from Section 3.2. It uses pre-created credentials to access the API, no remote registration is allowed for security reasons. In the scope of the described prototype, there are no options to control HA devices from the companion application yet, but with future updates, the API will allow manual interventions or automated rules to control grid devices.

A user can add new IoT devices to the subsystem using Home Assistant and the InfluxDB integration script replicates tracked sensors data into raw data bucket. On user set schedule InfluxDB runs data aggregation Flux (InfluxData Inc., USA) requests that write grouped sensors data into hourly bucket. Raw data bucket can automatically clean its data on schedule to reduce disk space usage after data aggregation. Caddy runs API application that provides authorized JWT token-based HTTPS read-only access to hourly InfluxDB bucket. The companion mobile application gets energy data from the API via REST requests to use in mobile forecasting model.

Each Docker container of the prototype has minimal required access level to users' data, saves secrets and credentials securely in encrypted state. External network access in controlled by firewall. Visualization of described prototype and its data flow is available in Fig. 6.

To validate the prototype, empirical tests were conducted:

– *System availability* was measured using system uptime scripts over 72 hours. Measured uptime was measured as 71 hours which it 97.2% of availability.

– *Collected sensors data volume per day:* connected sensors generated 1440 records (1 record per minute) each during 24-hour period which were grouped into 24 records of total consumption. Disk space consumed to save both raw and grouped data for 1 month is 104 Mb. Raw data buckets can be set to delete data on schedule, for example once per week to save disk space.

– *System load* – thermal state, average daily CPU load, and RAM usage were monitored using a Telegraf. Telegraf collected system load metrics every 10 seconds over 72 hours and stored them in InfluxDB. The average device temperature was 46.75°C, with a minimum of 44.1°C and a maximum of 51.25°C. The daily average CPU load was 18%, with peaks reaching 347% (given the quad-core architecture, the maximum load is 400%). Average RAM usage was 12% of the total 16 GB, remaining relatively stable within the range of 11–12.5%. These results indicate that a Raspberry Pi 5 with 16 GB RAM can reliably handle the current workload and still provides a substantial margin for scaling with additional sensors and integrations.

3.4. Discussion

The proposed LSTM short-term energy forecasting model and its conversion method demonstrated good prediction accuracy for the household consumer group. When compared with converted models for social infrastructure facilities and industrial enterprises from the previous research [8], the model shown similar load levels on CPU, RAM, and thermal state of the test device, as well as inference time less than 0.05 ms per forecast. The structure of the proposed model layers is similar to the LSTM model from the study [7], but hyperparameters and training process were optimized for further conversion to mobile formats. Unfortunately, these models can't be compared directly as they were trained on different household datasets and use different forecast horizons – 1 hour for the model in this paper, and from 6 hours to 3 days in [7], but the test results of the proposed model additionally confirm that these LSTM models can be effectively used for energy consumption predictions even on low-power devices.

When converted to CoreML and TensorFlow formats, this model can be deployed on edge devices, like smartphones on Android (Google Inc., USA) and iOS operating systems. Such deployment ensures that sensitive energy consumption data remains on the edge and helps consumers to make decisions on their smart grid operational modes without the use of expensive local servers and cloud computations. An additional benefit of such edge computations is that they reduce the load on cloud data centers, potentially decreasing their carbon dioxide footprint.

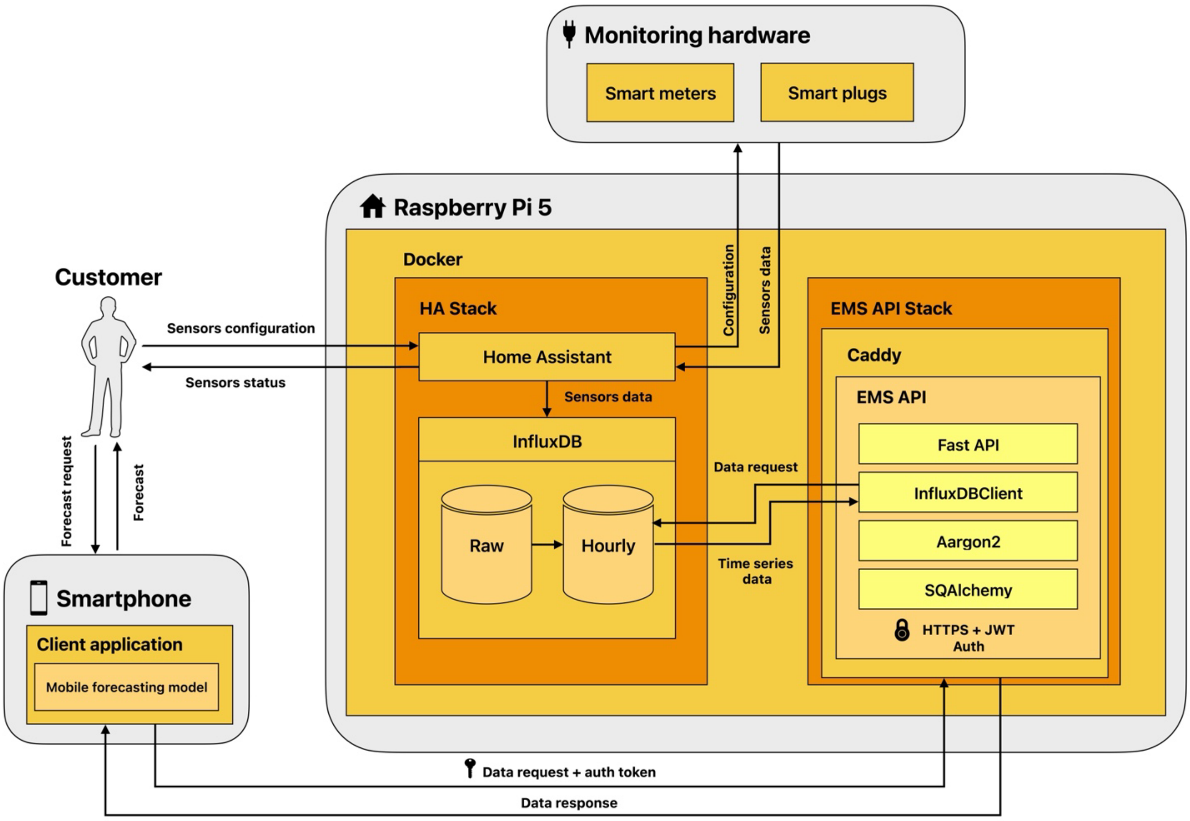


Fig. 6. HEMS data aggregation subsystem prototype structure

However, the study identified an important limitation: achieving high-quality forecasts requires significant amounts of historical consumption data. When such data is unavailable during early EMS integration stages, additional time is needed to fine-tune the model on collected data to produce meaningful results. Since on-device fine-tuning is not yet supported for LSTM models, a separate subsystem should be developed to enable model retraining on the edge as more customer-specific data becomes available.

The performance evaluation of the data aggregation subsystem prototype confirmed its robustness and suitability for edge environments, especially in the context of deployment in home networks. The subsystem demonstrated stable operation under continuous data streams and showed sufficient scalability to support extended sensor networks. When compared to other energy tracking systems that use HA, like [13], they are mainly focused on data visualization, integration with proprietary software of connected IoT devices, and are dependent on a cloud infrastructure. The prototype is not using cloud services and has better integration capabilities via protected API. In addition, it is specifically designed to store and prepare consumption data for forecasting models training. More complex EMS solutions built around HA usually have their own implementation of a data aggregation subsystem and even include forecasting modules. For example, EMHASS [14] allows to use InfluxDB for data aggregation as well as the suggested prototype. It also has the ML forecaster module that uses a regression ML model, which is overall not as effective as LSTM models [7], that the proposed prototype targets as a primary forecasting approach for integrations. In addition, EMHASS doesn't have the possibility to run ML models on smartphones natively. The prototype allows to build that integration and is specifically designed for it.

At the same time, the study revealed some usability limitations of the prototype. Initial setup requires a number of configuration steps that can be difficult for non-technical users, creating potential barriers to use in consumer environments. This issue highlights the importance of simplifying deployment procedures and improving integration workflows in future iterations of the system.

External factors also influenced the scope of testing. The restrictions imposed by martial law in Ukraine have limited the ability to test the developed solution in state infrastructure and enterprise environments, reducing the variety of operational scenarios available for evaluation. Expanding the test environment will be necessary to understand the system's full performance under different load profiles and security requirements.

Addressing the identified issues will involve enabling adaptive on-device learning, increasing ease of deployment for non-technical users, and further improving the forecasting and energy management subsystems regarding reliability and end-user trust.

4. Conclusions

1. The conducted analysis revealed that user trust in HEMS is formed through technical reliability, economic feasibility, environmental efficiency, and privacy protection. Results showed that users expect stable system operation, transparent control mechanisms, understandable interfaces, real financial and energy benefits. At the same time, the key barrier is the risk of data leakage and the feeling of loss of control, which affects the decision to share historical energy data necessary for accurate forecasting. The study confirmed that increasing trust is possible due to local data processing, minimizing dependence on the cloud, and ensuring transparent, predictable interactions with the system. As a result, a list of the most influential trust indicators was identified, which should be considered when developing modern HEMS, with a focus on the needs and expectations of the end user.

2. The proposed short-term household energy consumption forecasting model based on LSTM was developed and optimized for deployment on low-power devices. The conversion of the model

in CoreML and TensorFlow Lite formats ensured support for modern smartphones and stable forecasting accuracy (RMSE = 0.211 kWh) without degradation after conversion. Performance tests showed that both model formats demonstrate low execution time, minimal impact on processor load, and moderate RAM consumption. This confirms the possibility of applying the model in HEMS forecasting subsystems on smartphones to improve end users' trust.

3. The prototype of a data aggregation subsystem for HEMS based on open-source software tools was created and tested. It had been deployed to a Raspberry Pi 5 16 Gb and tested in a private household with 3 smart sockets connected for energy consumption tracking. Empirical testing of the developed HEMS data aggregation prototype demonstrated 97.2% system availability over 72 hours, stable performance with an average CPU load of 18%, RAM usage of 12%, and operating temperatures between 44–51°C. The prototype efficiently processed 4320 sensor records per day while consuming only 104 MB of monthly storage, confirming its reliability, scalability, and suitability for low-power edge environments. It was successfully integrated with an iOS companion application to provide energy consumption predictions. This confirms that the developed prototype can be used in future integrations with the forecasting subsystem. The prototype demonstrates real-world applicability using available open-source tools, which make it attractive to households and small businesses.

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Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, including financial, personal, authorship, or any other, that could affect the research and its results presented in this article.

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Data availability

The data that support the findings of this study are available from the upon reasonable request.

Use of artificial intelligence

The authors used artificial intelligence technologies within acceptable limits. Artificial intelligence tools were used in the manuscript preparation to meet disclosure requirements. In particular, ChatGPT (GPT-5) and Grammarly (version 2025) were used to verify grammar, spelling, and punctuation in the "Materials and Methods", "Discussion", and "Conclusions" sections without changes to their content. Scopus AI (version 2025) was used during the literature review process to search for relevant open-access sources and publications over the last decade using keywords provided by the authors of this paper. All results obtained using the specified tools were manually verified by the authors. The use of AI did not affect the content or conclusions of the study.

Authors' contribution

Anton Komin: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review and editing, Visualization, Project administration; ***Olha Boiko***: Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review and editing, Visualization, Supervision, Project administration, Funding acquisition.

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