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Design and implementation of a data-driven intelligent water heating system for an island community: A case study

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ABSTRACT

Water heating accounts for approximately 25% of household energy use in developed countries. Therefore, the optimal control of water heating through the deployment of intelligent residential Electric Water Heaters (EWH) brings significant benefits. This paper presents an innovative design and implementation of an easy-to-use device for intelligent residential water heating. The device relied upon machine learning techniques to forecast a consumer's hot water demand and optimize the operation of an EWH using a novel data collection process that relied on non-intrusive vibration data alone. The device was deployed in a six-month pilot project on the island of São Miguel, Portugal. The major difficulties were the novel use of vibration data to forecast the volume of hot water used and the uncertain behavior of the consumers. The challenges of only using vibration data were solved by careful data collection and artificial intelligence methods. To tackle the issue of uncertain consumer behavior, an innovative 'heat now' function was incorporated into the device to override the novel control framework. Results show that the device could accurately forecast hot water demand and optimally operate the EWH to meet this demand. The results showed an average reduction of 1.33 kWh/day per consumer, which equates to an average decrease of 35.5% in water heating costs. Calculations show that these devices can reduce the total energy used by 2832 kWh daily or 0.21% of total electricity generated. Furthermore, a fleet of these devices could reduce thermal generation by 0.37%, reducing emissions by 693.31 tons of CO_2 per year. The results from the consumer survey show that the device did not affect the consumer's comfort, validating the benefits and efficacy of the proposed device. Hence, the paper shows that a simple-to-use, novel device using an innovative forecasting algorithm based on non-intrusive vibration data brings numerous quantifiable benefits to actual consumers and electrical utilities.

1. Introduction

The ongoing shift towards the electrification of energy services, especially at a residential level, is an essential step towards the decarbonization of our society. This electrification is being driven by several factors, chief among them is the introduction of smart appliances and Home Energy Management Systems (HEMS) [23]. The increasing ability of previously passive residential loads, especially Electrical Water Heaters (EWHs), to actively participate in the energy system brings several benefits to many actors. Many factors, including increased automation, are driving this increased ability to intelligently control previously passive loads through artificial intelligence and machine learning, and the Internet of Things concept has formed the foundation of the so-called Internet of Energy, which allows various devices to work together to meet different load demands in an automated and intelligent manner, contributing to the clean energy transition [29]. The application of machine learning techniques is a rapidly evolving field of research, especially considering the applications to the energy sector. These techniques can extract powerful insights from historical data to help deal with uncertainty and data dynamics [27]. There is significant potential for advanced computing techniques, such as machine learning,

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Nomenclature

Abbreviation	Meaning
API	Application programming interface
CGPV	Pico Vermelho Geothermal Plant
CGRG	Ribeira Grande Geothermal Plant
CTCL	Caldeirão Thermoelectric Power Plant
DHW	Domestic Hot Water
DSO	Distribution System Operator
EDA	Electricidade dos Açores (Electrical utility of the Açores)
EWH	Electric Water Heater
HEMS	Home Energy Management System
LPG	Liquified Petroleum Gas
LSTM	Long Short-Term Memory
PEGR	Graminhais Wind Farm
XGBoost	Extreme Gradient Boosting

to be combined with connected devices and reforms in the electricity market to allow consumers to participate [45].

EWHs are high-potential devices for intelligent operation as they typically have high power consumption, operate in regular bursts of heating, and can store significant energy as hot water [9]. EWHs are fast-responding devices that do not require reactive power support as they use a resistive heating element [32]. Water heating uses approximately 25% of total residential energy consumption in developed countries [10]. Therefore, residential water heating is an important sector to optimize and can bring numerous benefits to various parties, especially if EWHs do the heating. These benefits can be allocated either upstream of the device or downstream. Upstream benefits can include reduced peak load through load shifting. This can lead to less energy being demanded at peak periods and intelligent heating during low-demand periods, which can also reduce the need for physical network infrastructure upgrades and an improved peak-to-average ratio [41]. The electrification of heating can lead to increased demand for electricity and the ability to heat during periods of high penetration of renewable energy, thus improving the utilization of these sources. Typically, electricity produced at peak periods is generated by more expensive peaker plants; therefore, reducing the peak load can have outsized benefits in terms of cost reductions. This is especially relevant for islands' power systems, as in this paper.

Furthermore, the intelligent electrification of residential water heating instead of gas in islanded power systems can also reduce the need to import costly fossil fuels to the islands, promoting energy security. Upstream benefits of these intelligent devices are accrued by various parties, such as distribution system operators (DSOs), energy retailers, and possibly aggregators or virtual power plant operators [19]. The downstream benefits of intelligent electrification of water heating are typically related to reduced energy costs and improved indoor air quality when the electric water heater replaces a natural gas water heater. Using gas to heat water is still very common, especially in Portugal, and thus replacing these heaters with intelligent electric water heaters can even increase access to clean and affordable energy services [34]. However, the quantification of both upstream and downstream benefits is somewhat unexplored, especially in small or island power systems, and therefore this is the main research gap addressed in this study. This paper presents an innovative design and implementation of an easy-to-use, low-cost device for intelligent water heating for residential consumption. To the best of the authors' knowledge is the first use of non-intrusive vibration data to forecast hot water flows using artificial intelligence techniques. Financial and environmental results from a six-month pilot project undertaken on the Azorean Island of São Miguel, in collaboration with the Electricidade dos Açores (EDA) utility, are presented. This smart plug harnesses the newfound ability to control residential EWHs intelligently and benefits both the consumer and the wider grid while ensuring that the consumer's desire for hot water and comfort is maintained.

1.1. Background and context

Before describing the design and implementation of the device for the intelligent operation of residential EWHs, this section provides background and context to the pilot project based in the Azores islands and Klugit energy, the developers of the device.

1.1.1. Azores islands

The Autonomous Region of the Azores is composed of nine islands that are widely dispersed and differ significantly in size. An image of the Azorean archipelago is shown in Fig. 1. These are isolated microsystems with no electrical connection between the islands. The nine islands utilize various electricity-generating technologies depending on each island's endogenous resources and demand. Due to their characteristics, these islands generally depend on fossil fuel thermal generation [4]. This dependence on imported fuels is due to various factors such as energy security and cost-effective means of production [40].

Each island has a main fossil-fuel-based generator which typically uses a diesel engine. There is, however, a growing desire to increase the penetration of renewable energy sources in the energy mix of the various islands, as can be seen by the 2030 Energy Strategy for the Azores published by the Regional Directorate of Energy of the Açores [30].

Currently, the most widely used renewable energy source in the Azores is geothermal energy, although it is only being exploited on two islands, São Miguel and Terceira. São Miguel has two geothermal plants, while Terceira only has one. Following geothermal, wind energy is the second most important renewable resource, with wind farms on all islands except Corvo. Hydropower is the next most developed renewable energy source, although it has the most extensive history of usage in the archipelago [15].

The focus of this study was on the island of São Miguel, and thus, a more in-depth discussion of its electricity mix is provided using data from the document '*Caracterização das Redes de Transporte e Distribuição*, 2019' [15]. At the end of 2020, there were twelve electricity-generating stations on the island. Chief among these plants is the Caldeirão Thermoelectric Power Plant (CTCL) which has an installed capacity of 98 MW and relies on fuel. The two geothermal plants, Ribeira Grande (CGRG) and Pico Vermelho (CGPV) have an installed capacity of 16.6 MW and 13 MW, respectively. The single wind farm, Graminhais (PEGR), has an installed capacity of 9 MW. Seven hydroelectric power plants have a combined installed capacity of 5.1 MW. There is also a single plant that relies on biogas for electricity production, the Musami Landfill Biogas to Energy Recovery Plant, and it has an installed capacity of 1.1 MW. In 2020, 422.15 GWh of electricity was delivered to the grid in São Miguel. Roughly 50% of this was from the thermal power plant, 40% from geothermal power plants, 6% from various hydroelectric power plants, and 4% from the wind farm.

1.1.2. Klugit energy

The smart plug was developed by Klugit Energy, a Portuguese start-up based in Aveiro. The device is used to convert a passive electric water heater into an intelligent device. This device consists of two components: a smart Wi-Fi-enabled plug that plugs into a regular wall power socket, and the EWH is plugged into the other side; the second is a connected water use detection sensor that clips onto the hot water outlet pipe of the EWH. Therefore, this device can be easily installed and requires no technical knowledge, extra tools, or modifications to the EWH unit. An example of an installed Klugit device is shown in Fig. 2, where the smart plug and the clip-on water use detection sensor are easily visible.

The Klugit device has been under development since 2018. The

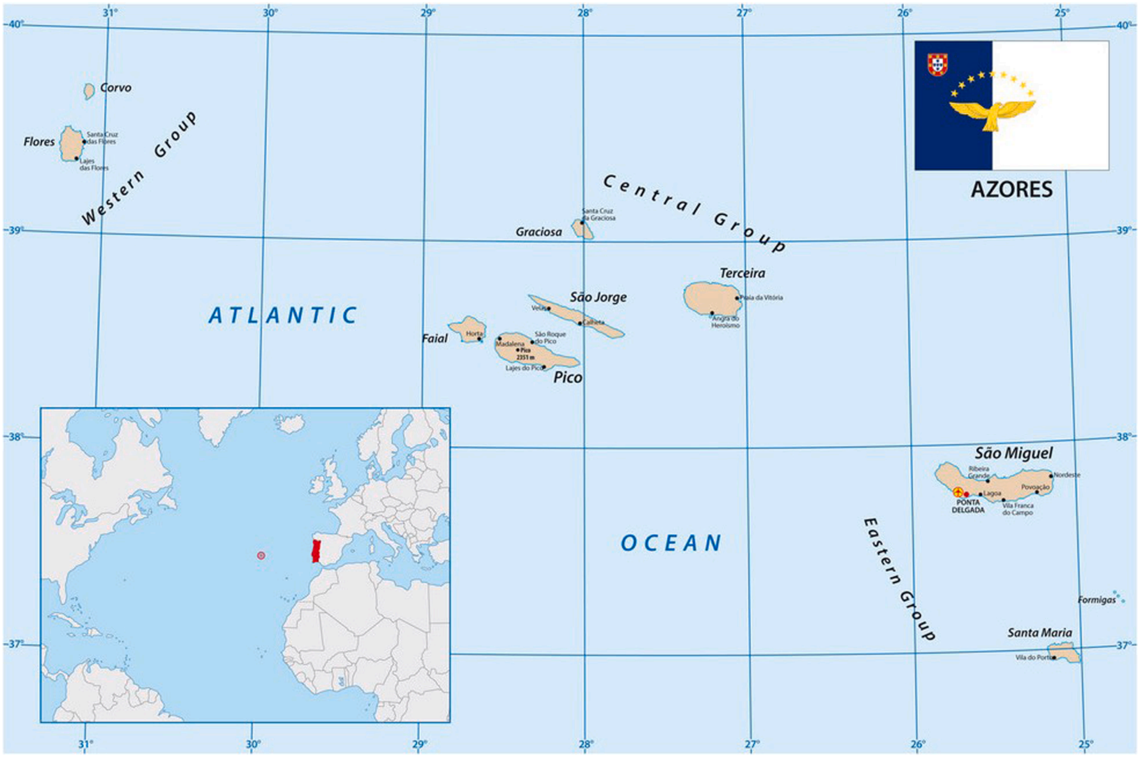

Fig. 1. Map of the Azores [1].

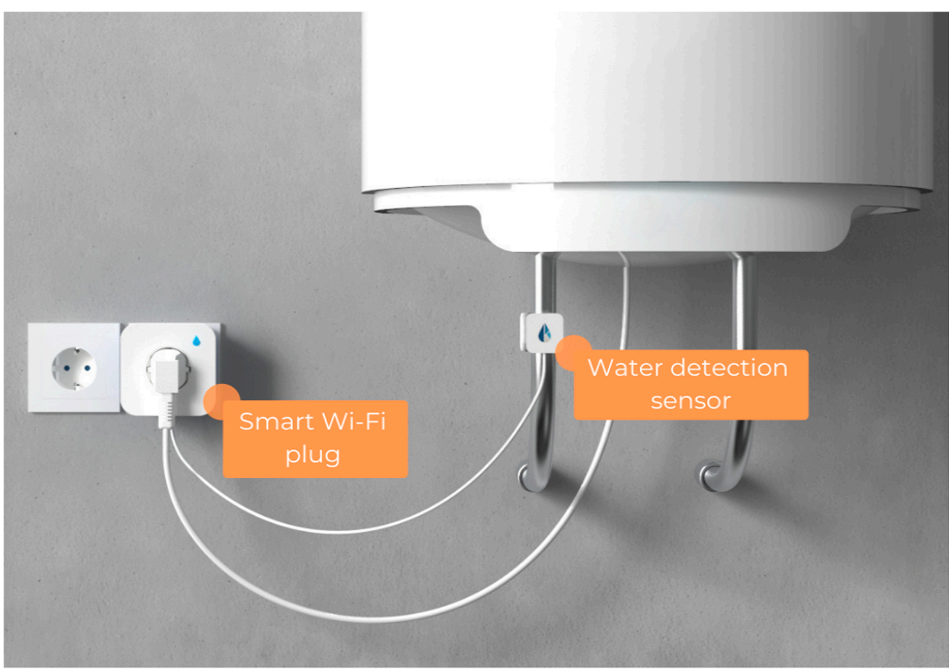

Fig. 2. Connected Klugit device.

prototypes were installed in 2020, and the first small-scale project was carried out in conjunction with E-REDES, the Portuguese DSO, in the town of Aveiro, Portugal. The results of this pilot project were positive and showed both the technical and economic benefits that the Klugit device could bring to both customers and DSOs [41]. The device allowed a reduction of energy use for the consumers and showed the potential to operate as a non-wires alternative to upgrading the physical infrastructure within low voltage networks. Based on this successful first pilot, a second, larger pilot was planned with EDA and commenced in July 2021. EDA is the overall system operator, managing the various electrical networks within the Autonomous Region of the Azores.

The work in the current paper builds upon the work done by Tavares et al. [41], where the prototype of the device was used in conjunction with intrusive temperature monitoring to manage the heating of a small number of EWH. At the time, the simplified model aimed to reduce the peak load of the local transformer in the distribution system, thus showing the device's potential to be a non-wires alternative to traditional infrastructure upgrades. Consumer comfort was not examined apart from a basic threshold to ensure the temperature in the EWH was above a certain setpoint. Consumer comfort and other major improvements such as the emission reduction potential, improved forecasting, non-intrusive monitoring and a larger pilot project were only included in the current paper.

1.2. Literature review

The idea of operating electric water heaters intelligently to benefit both the distribution operator and the consumer has been examined before [34]. However, previous studies tend to rely on intrusive monitoring techniques for water temperature and do not update the operation and control strategy of the EWH depending on the consumer's hot water usage. Moreover, these studies do not validate and implement their models in a real-world setting. EWHs can act as both domestic thermal storage and a controllable device that respond to real-time signals [10,18].

The potential of EWHs to benefit either the consumer or the DSO has been the subject of significant research in the past years. For example, a data-driven optimization model for the smart scheduling of EWHs was developed by Shen et al. [39] to meet several demand-side management requests. The authors utilize model predictive control (MPC) to develop a two-state EWH model and test it on real-world data consisting of 77 EWHs for 120 days. Results showed that costs were reduced by 33.2% and that anticipated domestic hot water demand met 97% of the actual demand during the day. These results were promising. However, there is no real-world testing of this model. In addition, even with the MPC framework, the temperature within the EWH still went below the lower comfort level set by the model. The ability of the model to avoid peak loads or to reduce emissions was not considered either.

The authors of Li et al. [27] developed a control method for various residential appliances based on artificial intelligence techniques. The approach is very interesting, but the authors rely on intrusive monitoring of the temperature of the EWH in contrast to the proposed model, which relies on a non-intrusive vibration sensor. This use of non-intrusive data collection is a novel contribution relative to the existing literature. The proposed method can develop a control policy using data obtained by interacting with the environment in a non-intrusive manner, simplifying the appliance's installation and operation.

Another promising residential appliance that can be utilized as an active asset in future energy systems is electric heaters with thermal storage. A day-ahead optimal control system for a single electric heater with thermal storage in an office building was developed by Mugnini et al. [31]. The goal was to operate the EWH to maximize the use of the onsite solar PV plant and, in turn, to minimize the amount of electricity used from the main grid. The control system was shown over two days. The authors used a mixed integer nonlinear programming technique to solve the system. The paper has two similarities to the current manuscript in that they authors test the system in a real-world setting and ensure the thermal comfort of the occupants. However, the present manuscript has the following novel contributions relative to the paper by Mugnini et al. [31]; the use of artificial intelligence forecasting techniques, consideration of the avoided generation, and thus avoided emissions brought about by the optimal control of the device.

A study that did investigate results from a real-world pilot project considering the demand response flexibility from smart appliances, including electric water heaters, was D'hulst et al. [12]. The study was based on a Belgian research project titled 'Large-scale implementation of smart grid technologies in distribution grids,' which examined residential demand response in the Flanders region of Belgium. The project prioritized user comfort over other technical objectives. The paper considered data from 15 residential EWHs, among other appliances. The developed system needed to be attached directly to the EWH and was not controllable by the consumer, as is the case in the device in the present study.

A study that focused on the benefits provided by intelligent EWH to the grid was conducted by Clarke et al. [9]. The authors used virtual devices to emulate real-world EWHs. A thermal model was used to estimate the EWH's temperature, and 100 virtual devices were emulated. The key results from this study were the high potential of EWH to engage in both frequency response and peak shaving services. The ability of the EWH to reduce costs by participating in these services or concerns relating to the comfort of the consumer was not considered in their study.

Mukherjee et al. [32] states that simplified thermal models do not adequately capture the dynamics of an EWH's operation, and using these simplified models can lead to incorrect planning and operating decisions by the electrical utilities. This proposed paper uses a data-driven approach that does not rely on the physical modeling of the EWH. The authors of Mukherjee et al. [32] utilize a thermal model of an EWH, which considers thermal stratification based on the characteristics of a single EWH. This choice may limit the ability of the model to be applied to other tanks easily, especially as the authors did not consider a sensitivity analysis based on variations of the physical characteristics.

The ability of EWHs to modify residential electricity consumption due to external incentives was investigated by Shah et al. [38]. Their paper used a simplified EWH model and hot water usage profiles of 450 apartments for 14 months with a 15-minute time granularity. Results showed a reduction in annual consumer costs by 33% and a significant ability to shift the heating load away from peak periods. No validation of the model in a laboratory or real-world setting was considered. In addition, the impacts on the consumer's comfort were not considered.

Yang et al. [45] develops a comprehensive model to investigate the impact of controllable devices HEMS considering time of use tariffs. However, the authors consider rigid control methods, especially for the EWH, which may not capture the dynamic behavior of the consumer. This dynamic behavior is considered in the proposed manuscript, which is a critical contribution relative to the work in Yang. Considering the dynamic behavior of the consumer reduces the input information needed from the consumer and adapts to changes in behavior automatically, thus providing a better experience for the consumer.

The paper authored by Tejero-Gómez and Bayod-Rújula [42] demonstrates and validates a simple and low-cost control module for the intelligent operation of an EWH. The authors used this system to minimize the home's water heating cost while respecting the user's comfort. Unfortunately, the system relied on a temperature monitoring probe to be inserted into the EWH. This may cause unnecessary complications for the user, such as requiring specialist installation or voiding the manufactures warranty. A single EWH is used as a case study in this paper, and the results show that the power used in high-tariff periods is reduced, and thus the cost of water heating is significantly reduced while maintaining the user's comfort levels. Another model that uses a heuristic algorithm to optimally schedule EWH under a dynamic pricing tariff is presented by Kapsalis et al. [24].

A paper that incorporated artificial intelligence techniques, notably an LSTM model, to forecast heat demand based solely on historical heating data was developed by Yao et al. [47]. The authors recognized that the LSTM model is one of the most powerful forecasting models for time-series data. The authors utilize only past heat demand forecasts as they state that auxiliary variables (such as weather data) are not always available or are of uncertain quality. In the current manuscript, the Klugit device obtains auxiliary data from the vibration sensor, and thus this data should be available, and the quality can be guaranteed. Therefore, the decision was taken in the current manuscript to utilize vibration data as an auxiliary variable to provide more data to the model. This decision is a significant novel contribution of the paper as, to the best of the authors' knowledge; this is the first time that hot water demand is being predicted using vibration data from the outlet pipe of the EWH using artificial intelligence techniques.

The papers discussed above show that intelligent electric water heaters have been studied. However, several shortcomings of these previous studies have been highlighted, and Table 1 shows how the current paper addresses those shortcomings in a real case study through several novel contributions with machine learning algorithms (XGBoost and LSTM) and considering consumer costs, peak load, consumer comfort, and emissions, relying on a non-intrusive strategy.

Through a careful review of the existing literature shown above, two gaps in the current knowledge were identified. Many papers either considered intrusive temperature measurements of the water inside an EWH or, on the other hand, only included historical demand data to forecast residential hot water demand. Both approaches have drawbacks, as mentioned above; therefore, the first knowledge gap concerns using data from non-intrusive measurements, such as vibration measurements, in a data-driven model to better forecast residential hot water demand. The second knowledge gap is that none of the papers in the literature review analyzed the complete set of benefits that the intelligent operation of an EWH can bring. Most papers consider either the cost-reduction potential of an intelligent EWH or the ability of the EWH to provide demand response or other ancillary services to the electrical utility. The actual value of intelligent EWH operation is not captured by focusing on only one benefit. Thus, this paper presents the quantification of several benefits from a pilot project, including cost reductions for consumers, avoided generation, reduced peak load, and avoided emissions. This comprehensive strategy addresses the second knowledge gap.

1.3. Contributions

Considering the context of the power system of the Açores and examining past literature in this field, the main contributions of this paper are the following:

- Design, validate, and implement a non-intrusive device to intelligently control electric water heaters in an easy and user-friendly manner.
- Development of a machine-learning algorithm to forecast residential hot water consumption based on non-intrusive vibration data alone. The model can use temperature data to identify the volume of water used. This was also used as the basis of the control method to intelligently control the device to ensure that the demand for hot water is met cost-efficiently and with no alterations to the EWH.
- Details and results of a pilot study where the device was implemented in 15 homes on the São Miguel island from July to December 2021.
- Results show the impact of intelligent heating on the consumer's energy bill, providing evidence that the consumer's comfort was not impacted through a survey conducted on the pilot study homes. This introduces essential qualitative information about the subjects' preferences, behavior, and comfort.
- Quantification of the results shows the impact of the device on consumer costs and avoided emissions. Additionally, the benefits of the device to the electrical utility are shown in terms of avoided costs of generation, avoided emissions, and impacts on physical infrastructure.

Based on the literature surveyed above, this paper aims to develop a first-of-its-kind commercially available device that optimally manages the operation of an EWH using machine learning model that utilizes non-intrusive vibration data., This paper presents several novel aspects regarding the optimal operation of EWH using non-intrusive data collection in a pilot study considering comfort, financial and environmental outcomes by combining the research gaps identified in the literature survey and the contributions previously mentioned.

Although challenging to develop, a model that relies on non-intrusive data is an important step forward as it reduces the cost and difficulty of installing devices based on intrusive in-line flow meters. Using a non-intrusive sensor also increases the number and type of EWH that can be retrofitted with the device, thus increasing its potential impact.

Even with the novel control technique for EWH, the major stumbling block of previous intelligent EWHs has been related to implementing the EWH in a real-world setting and showing that the comfort of the consumer is not affected. An example of this was demonstrated by Shen et al. [39], where the water temperature still went below the minimum set point temperature of their model, and in Clarke et al. [9] and Shah et al. [38], where the model was compared to water usage profiles but no actual validation of the model occurred in the real world and, additionally, consumer comfort was not even a consideration. Therefore, the inclusion of consumer comfort and the validation of the model in a six-month pilot project is novel compared to the literature surveyed above.

Finally, a significant difference to the existing literature is the consideration of thermal comfort, financial outcomes (for both the consumer and the electrical utility), and the environmental impact of the intelligent operation of an EWH in this pilot project. While D'hulst et al. [12], Kapsalis et al. [24] and Tejero-Gómez and Bayod-Rújula, [42] considered consumer comfort and cost, they did not show the financial and environmental impacts of intelligent EWH operation for the utility. These concerns are critical in small island power systems, as is the case of São Miguel, and therefore are included in this paper.

The rest of the paper is structured as follows: Section 2 details the methodology followed during the design and application of the machine learning-based control algorithm. The experimental validation of the

Table 1
Surveyed literature.

Paper	Type of control	Consumer cost	Peak load	Pilot project	Non-intrusive	Consumer comfort	Data set used	Emissions considered
[39]	Model predictive control	Yes	No	No	Not applicable	No	77 EWH for 120 days	No
[27]	LSTM	Yes	No	No	No	Yes	EWH Single	No
[12]	Linear programming	Not considered	Yes	Yes	Yes	Yes	15 EWH	No
[9]	Unspecified thermal model	No	Yes	No	No	No	Synthetic data	No
[32]	Thermal model	No	Yes	No	No	No	Single EWH	No
[38]	Greedy algorithm	Yes	Yes	No	Not applicable	No	450 apartments for 14 months	No
[42]	Heuristic	Yes	Yes	Yes	No	Yes	Actual data from single EWH	No
[47]	LSTM	No	No	No	Not applicable	No	Data from 1113 houses	No
[24]	Heuristic	Yes	No	No	No	Yes	Authors own	No
This paper	Machine learning algorithms (XGBoost, LSTM)	Yes	Yes	Yes	Yes	Yes	15 homes over six months	Yes

algorithm and device is also included in this section. The results of the case study are presented in Section 3. Finally, Section 4 contains the conclusions drawn from these results.

2. Data-Driven model for hot water prediction

This section introduces the methodology used in this paper. Initially, a section discussing the theoretical background is presented to provide an overview of the methods used. Following this, the details of the implementation of this methodology are given. There was a sequential methodology followed during the design of the device. The key parameter to identify was the Domestic Hot Water (DHW) demand throughout the day. This depended on several factors, such as the number of people living in the home, the day of the week, and ambient temperature. In addition, at the beginning of the pilot project, minimal data related to the DHW demand was available to be included in the prediction model. As a result, the methodology was split into different periods depending on the data available for the prediction model. Each period used a different technique to forecast the hot water demand of each household. These techniques were XGBoost and Long-Short-Term-Memory (LSTM) networks.

2.1. Theoretical background

This section introduces the data-driven techniques which were used to optimize and control the EWH. This section also contains the details of both the Extreme Gradient Boosting algorithm and the Long Short-term Memory network that were developed for this application.

As the problem of forecasting domestic hot water demand using non-intrusive techniques is a novel problem, several different machine learning techniques could be used. Because of this, an initial exploratory phase was carried out where several techniques were implemented and the results analyzed. This helped improve the results' quality as the best-performing models were chosen and refined. The models examined during this exploratory phase included decision trees, LSTM, XGBoost, K-means clustering, hierarchical clustering, random forest, and Support Vector Machines. Additionally, this exploratory phase helped avoid the cold start problem where the model cannot draw inferences due to insufficient information. The two models chosen were LSTM and XGBoost.

Following this exploratory phase, the decision was taken to use a two-stage approach with two different machine learning algorithms depending on the amount of data available. These were the XGBoost and Long Short-Term Memory algorithms. The advantages of XGBoost are that it is highly flexible, can be applied to problems using parallel processing, converges faster than regular gradient boosting techniques, and uses regularization to help avoid the risk of overfitting. The major disadvantage of this technique is that it does not perform well on sparse and unstructured data. Care was taken with the data obtained from the Klugit devices to minimize this disadvantage.

In the second stage, the LSTM model was applied to the problem. There are several advantages of this model, especially when analyzing sequential data. This is due to their ability to formulate high-level representations of complex data, which better captures the structure of the data relative to other recurrent neural networks. Other advantages of the LSTM model include their ability to remember information for extended periods, allowing them to handle long-term dependencies in the data. Finally, the LSTM model is less susceptible to the vanishing gradient problem because it uses the LSTM cell as the activation function, which preserves information across more prolonged periods. These two models are discussed in detail in the following sections.

2.1.1. Extreme gradient boosting (XGBoost) algorithm

Once sufficient data was collected for the household from the clip-on vibration sensor, the Extreme Gradient Boosting (XGBoost) algorithm was used to forecast hot water consumption. XGBoost is a widely used tree-boosting system [8]. XGBoost is a highly scalable machine learning system that uses several adjustments to traditional tree-boosting algorithms. These adjustments provide the ability to handle sparse data, a proven procedure for handling weights for efficient proposal calculations. These improvements lead to a powerful tree-boosting solution successfully deployed in many real-world applications. A python interface of XGBoost was used in this paper [35].

The XGBoost algorithm is based on several decision trees, with each tree being generated through a gradient descent method. The algorithm's objective is to minimize a particular objective function subject to a second-order Taylor expansion. To reduce overfitting, the XGBoost utilizes the complexity function of the tree to represent the objective function's constant term. The mathematical formulation of the XGBoost algorithm, represented by Equations (1) to (4), is taken from [8]:

$$Object(t) = \sum_{i=1}^{n} l\left(y_i, \widehat{y}_i^t\right) + \Omega(f_t) + C \tag{1}$$

$$\widehat{y}_i^t = \widehat{y}_i^{t-1} + f_t(x_i) \tag{2}$$

$$\Omega(f_t) = \gamma T_t + \frac{1}{2}\lambda \|w\|^2 \tag{3}$$

In the equations above, l is a differentiable convex function that calculates the gap between the prediction $\widehat{y}_i^t$ and the true value y_i. $\Omega(f_t)$ is a penalty function that increases as the complexity of the model grows to reduce overfitting, and C represents a constant. In Eq (2), $x_i$represents the input vector, and the actual value of hot water demand is shown by y_i while the predicted value of hot water demand is shown by $\widehat{y}_i^t$. In Eq (3), the number of leaves in the tree is shown by T_t. The square loss function is represented by $\gamma$and λ. w is the leaf weight. Using the Taylor expansion, we can approximate the $Object(\bullet)$ by the following:

$$Object(t) \approx \sum_{i=1}^{n} \left[l\left(y_i, \widehat{y}_i^t\right) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right] + \Omega(f_t) + C \tag{4}$$

where $g_i$and $\frac{1}{2}h_i$ represent the coefficients of the first and quadratic terms of the Taylor expansion, respectively.

2.1.2. Long Short-Term Memory (LSTM) algorithm

Once sufficient data was collected regarding the hot water usage of the consumers, the XGBoost algorithm was replaced by a Long Short-Term Memory (LSTM) algorithm. This was done due to the superior accuracy of the LSTM model [21]. LSTMs utilize feedback connections, and this property enables LSTMs to process entire sequences of data without treating each point independently. Instead, the LSTM retains valuable information about previous data in the sequence to help process new data points. As a result, LSTMs are particularly good at processing time series data, which is a significant factor in selecting this technique for this paper. LSTM models have been successfully implemented in the energy sector [20;46]. However, the LSTM technique has been widely and successfully applied to practical applications in other fields outside of electrical energy systems. For example, researchers used LSTM models in conjunction with other techniques to develop a spatiotemporal model to analyze the temperature distributions in various thermal processes [17]. The model was applied to the curing process within semiconductor manufacturing, and the results show that the model performed well. Another example of the LSTM model being used in a real-world context is presented by [3]. In the paper, the authors developed a deep-learning neural network to identify different carp species. The model used a 5-fold cross-validation process and achieved an accuracy of 100%.

A bidirectional-LSTM model was developed by [44] to formulate an optimal gear-shifting strategy for manual transmission systems of heavy-duty trucks working in mines. The bidirectional LSTM model was prepared by backpropagating an LSTM model to combine forward and backward information simultaneously. The model achieved an accuracy of 95.8% and could operate with high speed to meet the demands of the transmission's operation. A final application of LSTM models to real-world applications is shown in [7], where an LSTM model was used for rainfall prediction. The LSTM model outperformed other data-driven models, namely a random forest algorithm, and could be rapidly applied to various climatic areas across the globe. Despite the increase in the predictive ability of the LSTM model, this algorithm also required a considerable amount of data for training and testing, hence the decision to first use the XGBoost model until sufficient data were available. Seven LSTM models were trained, one for each day of the week.

A typical LSTM model consists of several sub-networks which are recurrently connected [37]. These sub-networks are known as memory blocks. These memory blocks maintain their state over time and regulate the information flow through the non-linear gating units. Conceptually, an LSTM model is composed of several processing blocks and inputs. The interaction between these components is discussed below in Fig. 3.

The initial step is an input that uses the output of the previous LSTM unit and the current input cell. This is expressed as after [43]:

$$z^{(t)} = g\left(W_z x^{(t)} + R_z y^{(t-1)} + b_z\right) \tag{5}$$

In the above equation, W_z and R_z are weights associated with $x^{(t)}$ and $y^{(t-1)}$ respectively and the bias weight vector is denoted as b_z (Van Houdt et al., 2020). The next step is to update the input gate, which combines the current input × and the previous LSTM unity-1 with the cell value c of the prior iteration.

Van Houdt et al. (2020) showed this as Equation (6).

$$i^{(t)} = \sigma\left(W_i x^{(t)} + R_i y^{(t-1)} + p_i \odot c^{(t-1)} + b_i\right) \tag{6}$$

where W_i, R_i and p_i are weights associated with $x^{(t)}$, $y^{(t-1)}$ and $c^{(t-1)}$ respectively for this component. The bias weight vector is represented by b_i. The gate activation function is represented by σ. The LSTM layer determines how much information is retained in the cell states $c^{(t)}$from the previous steps. The vectors p_i and $c^{(t-1)}$ are multiplied using point-wise multiplication ($\odot$). This layer also considers the selection of the candidate values, $z^{(t)}$,which may be added to the cell states as well as the input gate activation values, $i^{(t)}$.

The following essential aspect of the LSTM cell is the forget gate in which a decision about how much information to remove from the previous cell state, $c^{(t-1)}$, is removed. In this step, the activation values, $f^{(t)}$, of the forget gates are calculated using the current input, $x^{(t)}$, the outputs from the previous time step, $y^{(t-1)}$, and the previous memory cell state, $c^{(t-1)}$, the peephole connection and the terms representing the bias, b_f. This is shown as, after (Van Houdt et al., 2020):

$$f^{(t)} = \sigma\left(W_f x^{(t)} + R_f y^{(t-1)} + p_f \odot c^{(t-1)} + b_f\right) \tag{7}$$

where W_f, R_f, and p_f are weights associated with $x^{(t)}$,$y^{(t-1)}$ and $c^{(t-1)}$ respectively and the bias weight vector is denoted as b_f. The next step is to compute the cell value. This step uses the outputs of the block input, $z^{(t)}$, the input gate, $i^{(t)}$, and the forget gate, $f^{(t)}$ as well as the previous cell value. Van Houdt et al. (2020) represented this as:

$$c^{(t)} = z^{(t)} \odot i^{(t)} + c^{(t-1)} \odot i^{(t)} \tag{8}$$

The subsequent output to be calculated is the output gate which combines the current input, $x^{(t)}$, the result of the last LSTM unit, $y^{(t-1)}$as well as the cell value, $c^{(t-1)}$. Visually, this is represented after (Van Houdt et al., 2020):

$$o^{(t)} = \sigma\left(W_o x^{(t)} + R_o y^{(t-1)} + p_o \odot c^{(t-1)} + b_o\right) \tag{9}$$

where W_o, R_o, and p_o are weights associated with $x^{(t)}$,$y^{(t-1)}$ and $c^{(t-1)}$ respectively and the bias weight vector is denoted as b_o. The final step is the calculate the block output. This combines the current cell value and the current output gate. This was represented by Van Houdt et al. (2020) as:

$$y^{(t)} = g(c^{(t)}) \odot o^{(t)} \tag{10}$$

2.2. Deployment

The data was collected by a non-intrusive temperature sensor attached to the hot water outlet pipe of the EWH. In the pilot project in São Miguel, only the temperature data was collected from the various EWHs. In a previous pilot project to validate the proof of concept, water flow data was also collected, and the model was initially validated against this last data. This was used to train the temperature-to-flow converter model, but in the current pilot project, only the temperature data were collected and utilized.

2.2.1. Temperature to flow converter model,

The first model uses previously available flow data and the chronologically corresponding temperature data to train a model that predicts whether there was significant flow in a given time interval, generating either 1 or 0 for a specific moment. The flow and processing of data in this model are shown in Fig. 4. The model pipeline presented in Fig. 4 is a minimalistic view of the training steps for each model. The initial datasets are used as input for the models (temperature data obtained from the previous pilot project), and the output was the validated flow data learned from this data. A vital advantage of this pipeline is the discretization of the time steps to two-minute binary windows. This was obtained through experimentation of different periods. The two-minute windows provided the best compromise between accuracy and water usage prediction. The water usage prediction relied on clusters of true positive forecasts instead of a single true positive value. This was done to

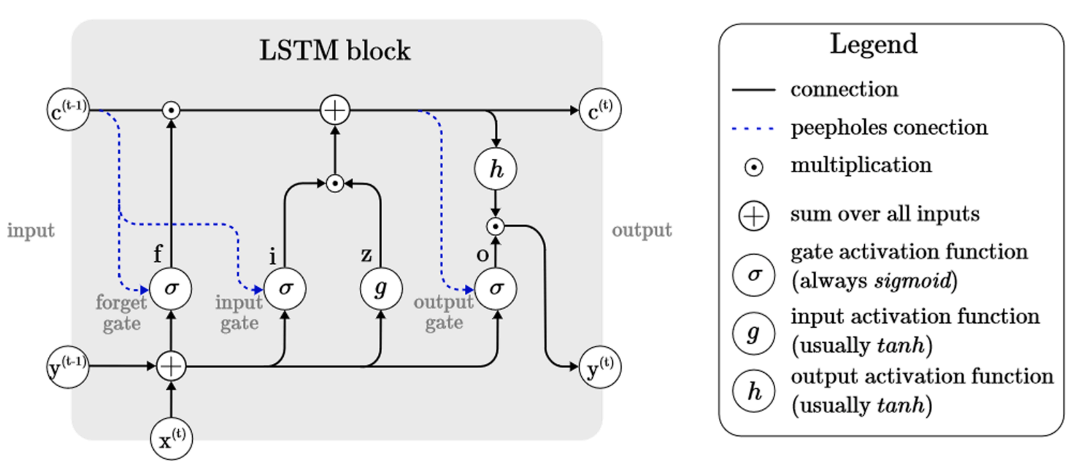

Fig. 3. Structure of a vanilla LSTM model [43].

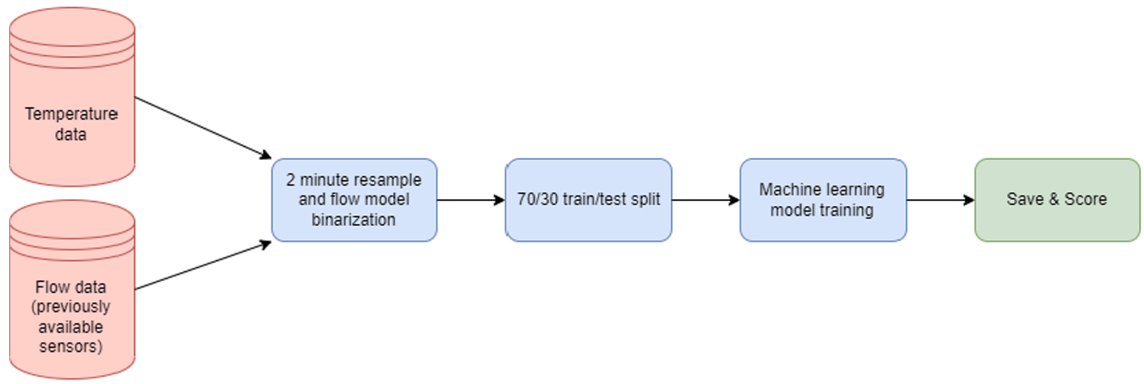

Fig. 4. Pipeline for the temperature-to-flow converter model.

minimize the heating of the EWH while ensuring the consumer's comfort.

Each model was trained and validated five times using different training and validation data, especially during the hyperparameter search phase. The five sets of training and validation data were prepared before the hyperparameter search and used across all models. The training and validation sets were obtained from larger datasets during the later tuning phase. The size of the training and validation datasets was determined according to the size of the search space and the time to train each model.

The selected sampling rate was two minutes. The issue of whether the ratio between the sampled flow duration and actual flow duration was significantly different in the predicted and actual flow data was studied, and it was concluded that there was only a significant difference if the sampling rate was greater or equal to three minutes, meaning any value lower than three minutes is appropriate. For values of the sampling rate lower than three minutes, there was no significant change in the ratio, as mentioned above. Interestingly, the results obtained when using two minutes were better than when a sampling rate of one minute was used. The machine learning model uses a neural network with the structure shown in Table 2. The design of the model and the hyperparameters were determined through a multi-level grid search. This search used larger increments of the values for the hyperparameters in the initial stages of the search, and then when the search space had been narrowed down, the multi-level grid search used much smaller increments of the hyperparameters to fine-tune the structure of the model rapidly. The final choice of the design of the model was based solely on the results of the F-Score assessment.

The model was trained for 70 epochs with a batch size of 128. The learning rate was set at 0.0001, and a validation split of 0.2 was used. The loss was computed using a custom function that allows different weights for the two classes to be applied to a typical binary categorical cross-entropy function. The weights applied made the loss function penalize false negatives twice as much in the best-performing model that was trained. This was done to compensate for the fact that there is a substantial discrepancy between the number of samples of each class.

Table 2
Temperature to flow convertor's neural network structure and parameters.

Layer number	Layer type	Parameters
1	1D Convolutional	Filters: 64, Kernel size: 3
	Batch normalization	–
	Rectified Linear Activation Function	–
2	1D Convolutional	Filters: 64, Kernel size: 3
	Batch normalization	–
	Rectified Linear Activation Function	–
3	1D Convolutional	Filters: 64, Kernel size: 3
	Batch normalization	–
	Rectified Linear Activation Function	–
4	1D Global average pooling	–
5	Dense	Neurons: 2, Activation: softmax

The Rectified Linear Activation Function (ReLU) was used to transform the weighted sum of the inputs of a specific node into that same node's activation or output. The ReLU is a piecewise linear function, a popular default neural network activation function that helps improve model performance [2]. The main motivations for using this parameter in the model are simple computation, sparse representation, and linear behavior.

After each layer, a batch normalization procedure is carried out. This process ensures that all features are constrained to the same scale. This process is done to ensure that a single feature does not dominate the model and can help speed up the convergence of the LSTM model [22]. Models with several layers may be sensitive to the initial random weights assigned to the inputs, and batch normalization helps standardize a layer's inputs. Batch normalization helps to reduce the number of training epochs that would have otherwise been needed.

The first three layers of the LSTM use a 1D convolution layer. This type of layer is especially applicable to time series data [26]. The fourth layer utilizes global average pooling to replace the other fully connected layers in the LSTM [28]. Global pooling takes the average of each feature map and creates a vector that is sent directly to the softmax activation layer. In this layer, there is no parameter to optimize; therefore, overfitting is avoided. The final layer is a dense layer, so called because each neuron in the layer is connected to all other neurons in the next layer. The output of this layer is the dot product of all inputs and their corresponding weights and relies on the choice of the activation function [5].

In this paper, the softmax activation function was used. As mentioned above, this function takes the vector of numbers and converts them into a vector of probabilities proportional to each value's relative weight [6]. It is a popular activation function for problems in machine learning [33].

The performance of various iterations of this model with these and different parameters was tested using the F-Score for the test set. A multi-level grid search was performed, using different values for all parameters mentioned above and testing the final F-Score for each. The process followed for selecting the hyperparameters was a multi-layer grid search. This approach uses various levels of increments for the hyperparameter search. In the first iterations, the increments between the values were larger than those in the later iterations. This allowed for rapid convergence of the hyperparameter values and easier fine-tuning in the final stages of the model development. The advantage of using the grid search was reducing the number of configurations required to be tested, versus, for instance, testing every combination of parameters. Performing the multi-level grid search further reduced the number of tested designs while at the same time allowing for more precise fine-tuning. The best model obtained from this multi-layer grid search had an F-Score of 0.77 and was saved for later use in the relevant hot water usage prediction model, as shown in Fig. 5.

The model aims to forecast the timing and quantity of hot water demanded by the household. Therefore, the false positives and negatives are the most relevant metric to analyze the model's performance. Some of the best-performing models from the exploratory phase were trained to forecast hot water demand in two-minute intervals, but the final choice of whether or not to activate the EWH to heat the water will also depend on the quantity of water demanded, and this was inferred from the number of usage intervals predicted by the model. Therefore, clusters of true positive values are critical for the optimal performance of the model. Clustered false positives could lead to instances of EWH heating when there was no actual water demand, increasing the energy used. The F score metric was chosen during the hyperparameter search phase as it best fits the requirements to assess the true positives and false positive results. Other scoring metrics, such as the Root Mean Square Error (RMSE), were utilized as well, for example, when the flow volume metrics were required. During the hyperparameter search phase, when the number of models to train, validate and compare was large, F-Score was the scoring method that best suited the requirements of the problem.

2.2.2. Relevant hot water usage prediction model

This model predicts the relevant water usage for a set of days the user provides. It is used to make predictions about when water needs to be heated. The structure of the hot water prediction model is shown in Fig. 6. The figure shows how the temperature data creates and uses various predictive models. Three different models were used to forecast the hot water demand depending on the data available for that specific device. First, a linear regression model was used to identify the mean daily hot water demand profile. After this stage, the XGBoost model was used until six weeks of data were available, and finally, the LSTM model was used after six weeks. Once the model had been created, trained, and saved, it could be used to forecast the periods of hot water demand for

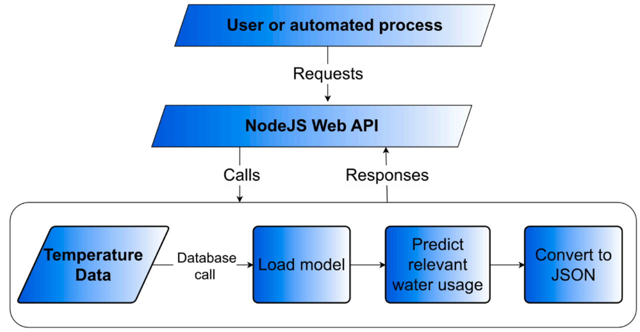

Fig. 6. Pipeline for obtaining the predicted relevant hot water usage for a day.

the consumers. This is shown in Fig. 6, where a request would be sent to the application programming interface (API), which would call the relevant model to forecast the hot water demand. The forecast is made and sent back as a response to the API, which sends it to the device. Then the decision is taken whether or not to heat the water to meet the forecast demand.

Three types of models are used, which are: Means, XGBoost, and LSTM. The Means model is used when we have a low number of samples and training a model is not yet viable. Using a Mean Shift model, it identifies which hours were relevant hot water usage in the last few weeks. The XGBoost model minimizes the squared error and uses 1000 estimators. The LSTM model comprises seven models, one for each day of the week. Each model is trained individually but with the same parameters. Each model consists of 32 LSTM units, followed by a Dropout layer that drops 20% of the results and a final dense layer of 24 neurons (one for each hour) that uses a softsign activation function in the version designed for flow data. When using temperature data, an activation function is not necessary as the temperature data is normalized before it is used as input into the network. The data is rescaled afterward to reconstruct the temperature data. This approach was not appropriate for the flow data, as it is binary, so an activation function that allowed some

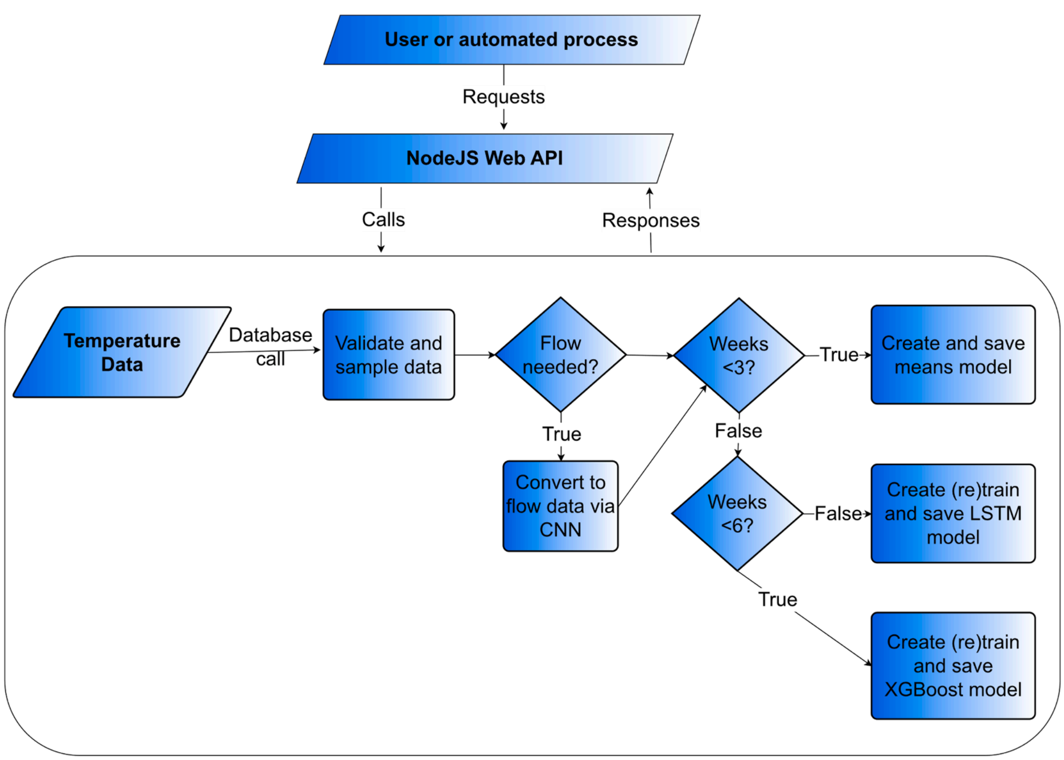

Fig. 5. Pipeline for training the relevant hot water usage prediction model.

progression, such as the softsign, was necessary. The Adam optimizer optimized both temperature and flow versions. The Adam optimizer is an alternative to classical stochastic optimization in deep learning problems. It combines the advantages of two other stochastic gradient descent extensions. These other extensions are the Adaptive Gradient Algorithm and the Root Mean Square Propagation [36]. Further details of the Adam algorithm can be found in [25], but, in summary, the Adam algorithm achieves good results quickly and emerged as an excellent overall choice of algorithm for deep learning applications [36]. In terms of loss functions, the temperature model used the Mean Square Error model, while the Flow model relied on the Squared Hinge model.

After applying these models, the times of significant hot water usage need to be identified. The temperature model identifies these times, and the results are evaluated using the Root Mean Square Error Model for the first iterations, and afterward, the F-Score model was applied. During the pilot project, the model was under continuous evaluation and improvement. One such improvement is the flow model. The flow model is an extension of the temperature model; in this model, the duration of the flow can also be forecasted. The performance of the flow model was compared to the values obtained by the temperature model. For this comparison, the ratio of the correct predictions against the accurate predictions plus incorrect predictions was used for all periods where water flow was predicted.

The following two figures, Fig. 7 and Fig. 8, show the improvement of the flow duration model for the XGBoost and LSTM methods across ten experiments. The flow model outperformed the previous temperature model in each experiment and for both machine learning techniques. This new method also provides additional information regarding the total quantity of hot water used, which can be reported to consumers to increase their knowledge of water usage. The choice of adding an estimation of the flow of water was made during the pilot project, and the results show that this choice improves the model results.

2.3. Digital infrastructure design

The models introduced above were incorporated into a broader digital infrastructure. This infrastructure allowed the devices to gather the data, communicate this data to the server and receive control signals from the server. The infrastructure used in this system is presented in Fig. 9. The relevant services and applications are shown with the flow of the information displayed via the black arrows. The device is depicted as the Klugit Unit in the bottom left of the figure.

3. Case study

This section contains the details of the case study implemented in São

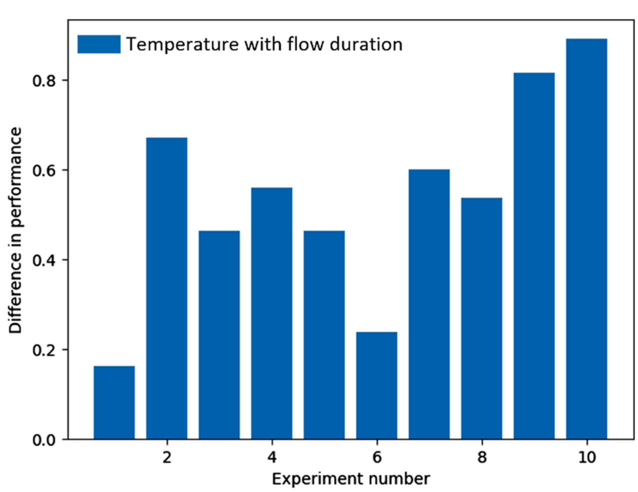

Fig. 7. Improvement in the performance of the final XGBoost flow model.

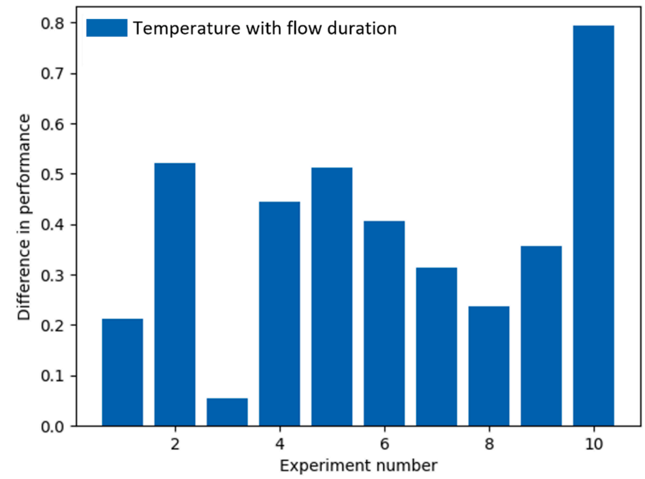

Fig. 8. Improvement in the performance of the final LSTM flow model.

Miguel between July and December 2021. São Miguel was selected as the location of the pilot project after discussions with Electricidade dos Açores (EDA). The homes selected for the project were in fact the homes of employees of EDA who chose to participate in this pilot project. São Miguel is the largest island of the Açores and has been used in previous research projects. Other islands within the Açores may be alternatives for future projects. The islands share a similar climate and other characteristics which mean that the results obtained in this pilot project can be representative of the other islands.

The devices were installed in 15 homes, and a photo of a typical installation is shown in Fig. 10 below. The types of homes and equipment installed varied widely across the houses. The number of inhabitants ranged from two to five people in the home, while the capacity of the EWH ranged from 80 to 150 l. A standard installation and training process was done for each household. The device was controlled by a smartphone app, allowing users to monitor hot water usage, and included a ‘heat now’ option. A screenshot from the app is shown in Fig. 11. This option allowed the users to override the smart mode and immediately heat the water in the tank up to a particular set point. This option provided the users with increased control and flexibility.

The smart mode is the main novelty of the Klugit device as it converts a previously passive EWH into an active grid asset that takes several inputs and intelligently operates the EWH to minimize the heating cost of the consumers while ensuring their needs for hot water are met. Three aspects influence the operation of the smart mode. The first is the tariff regime in place for the consumer. The smart mode aims to minimize the energy consumed from the high tariff periods while maintaining the consumer’s comfort. The second aspect of the smart mode is related to the forecast of the hot water demand needed by the household. This forecast relies on artificial intelligence techniques to accurately forecast the quantity of hot water based on the past behavior of the home. The final influencing factor of the smart mode is the temperature of the water stored in the EWH, which also relies on the amount of water used in the previous periods and physical characteristics relating to the EWH itself.

The smart mode helps to reduce energy consumption and therefore costs by maximizing the amount of heating taking place during low tariff periods, and only in exceptional circumstances, such as if the user chooses the ‘heat now’ option, will the smart mode heat water during high tariff periods. The physical reasons for this are that less electricity is being consumed in high tariff periods and the heating load is being met during lower tariff periods, and the EWH effectively stores this water until it is needed, which helps ensure that the consumer’s comfort is maintained.

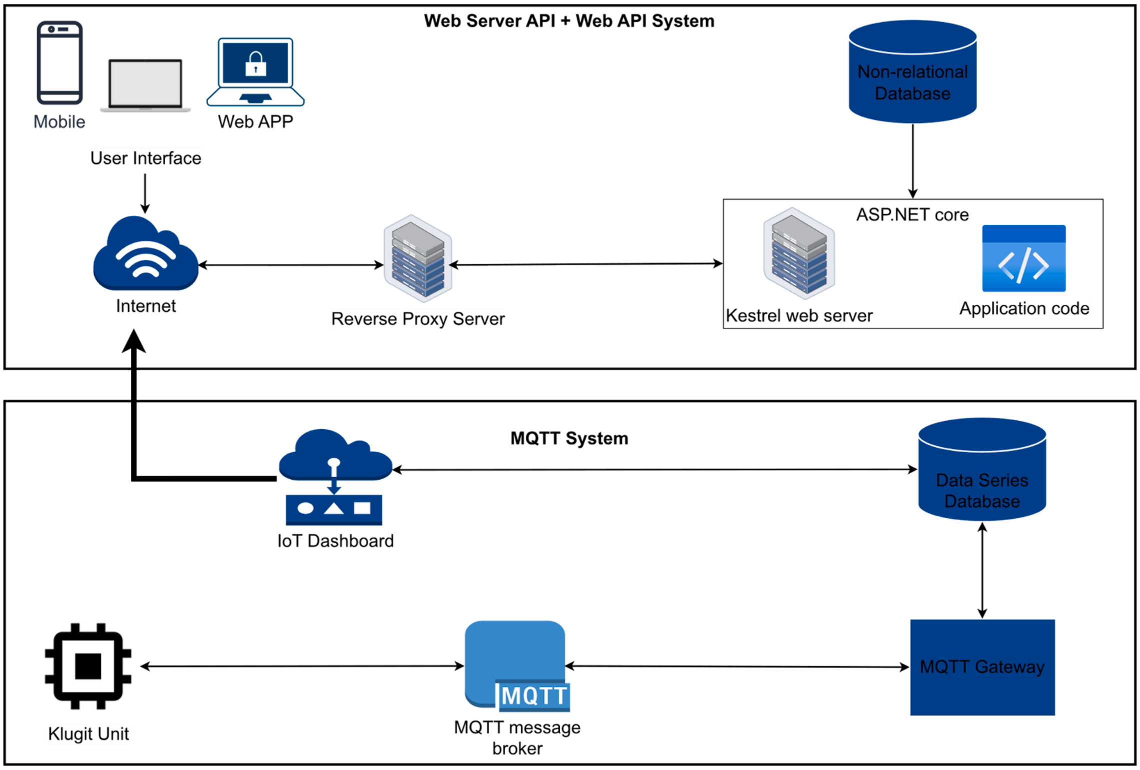

Fig. 9. Infrastructure layout of the Klugit system.

Fig. 10. Typical installation of a Klugit device.

4. Results

This section presents the quantitative results of hot water forecasting, peak load reduction, and avoided emissions. In addition, the qualitative results of consumer interviews and surveys are presented. These surveys are included to help evaluate the impact of the devices on consumers' lifestyles and comfort.

4.1. Hot water forecasting and intelligent heating

The core function of the device is to forecast residential hot water demand and to activate the EWH to meet this demand intelligently. This intelligent heating can help reduce unnecessary heating cycles of the EWH, thus reducing thermal losses and shifting the heating periods away from periods of high tariffs. These two benefits accrue to the consumer, but the device can also offer benefits upstream to the system operator. These benefits may include peak shaving, load shifting, participation in demand response programs, and ancillary services. In this pilot project, only the first two benefits were assessed.

In addition to the abovementioned benefits, there is also the ability of the device to operate during high periods of renewable energy generation. By operating during these periods, the device can help increase the penetration of renewable energy technologies and utilize energy that may be curtailed if the device is not functioning. To demonstrate the impact of the device on the operation of an EWH, Fig. 12 compares the baseline operation for the average of July and August without any intervention for the same months. In Fig. 12, the blue line shows the baseline operation of EWH without the operation of the device. The orange line shows the device operating in the smart mode to heat the water intelligently when needed. From the Figure, it is clear that the heating load has been shifted out to the early morning and late afternoon periods, avoiding the early evening peak. This intelligent load heating results in a reduction in the electricity used. There is a significant period of pre-heating done in the morning and again between 16:00 and 17:00. This helps reduce the need for heating at other high-peak demand periods.

The heating load was reduced by an average of 1.33 kWh/day per device for all devices, representing an average reduction in heating demand of 26.43%. The maximum decrease in heating use was 54.4% for a single household, while one home saw the heating demand increase by 2.24%. This specific case is discussed in detail in the following

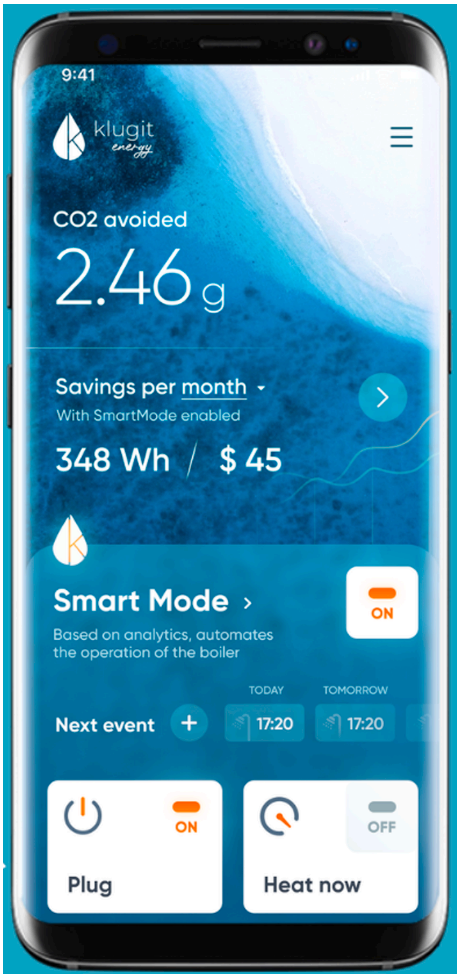

Fig. 11. Screenshot of the Klugit energy app.

paragraphs. The average daily energy use in the baseline and smart mode of the ten devices with the most recorded data during the pilot period are shown in Table 3. The device names have been removed for data privacy reasons. The table shows a considerable reduction in the energy use associated with domestic hot water use. In addition to reducing the electricity used for water heating, the Klugit device also shifts the heating timing to periods with low energy tariffs, reducing the consumer's energy bill.

In São Miguel, a three-period tariff regime is available for the clients. There are periods of low, moderate, and high energy tariffs depending on the time of day. These tariffs are shown in Table 4 below. These costs are distributed over the entire day, periods of which are related to the demand for electricity in the regulated energy market. The low tariff corresponds to the periods where the electricity demand is less; the moderate tariff corresponds to the periods where there is medium demand; the high tariff corresponds to the periods where the peak load is observed, which means the electricity demand is at the highest.

The tariff is overlaid in Fig. 13 below, which shows the average baseline and smart mode operation for a given home. The green area represents periods of a low tariff, the yellow indicates periods with moderate tariff, and the red denotes the periods with a high tariff. Again, the blue curve represents baseline mode operation, and the orange curve represents smart mode operation.

Fig. 13 shows that in the smart mode operation, there is more electricity used by the EWH in low or medium tariffs compared to the baseline operation. The smart mode operation reduces the energy cost to consumers by combining the effects of reducing energy consumption and switching the heating load from high tariff periods to low tariff periods. Based on the tariffs in place and Fig. 13, consumers would pay

Table 3
Energy use differences.

Device	Baseline (kWh)	Smart mode (kWh)	% reduction
1	10.09	8.79	12.88
2	2.52	2.22	11.90
3	5.03	3.51	30.22
4	4.61	3.37	27.84
5	2.9	2.14	26.21
6	7.78	4.82	38.05
7	4.23	2.92	31.78
8	5	2.28	54.40
9	4.46	4.56	−2.24
10	3.75	2.41	35.73

Table 4
Tariffs in use during the pilot project.

Tariff Type	Low	Moderate	High
Cost (€/kWh)	0.10	0.16	0.23

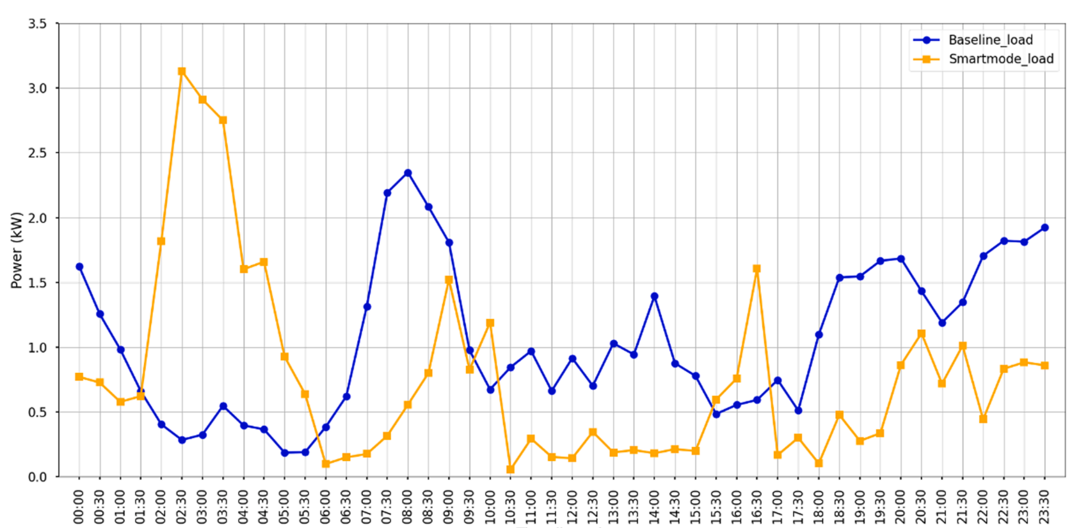

Fig. 12. Energy use in both smart mode and baseline modes.

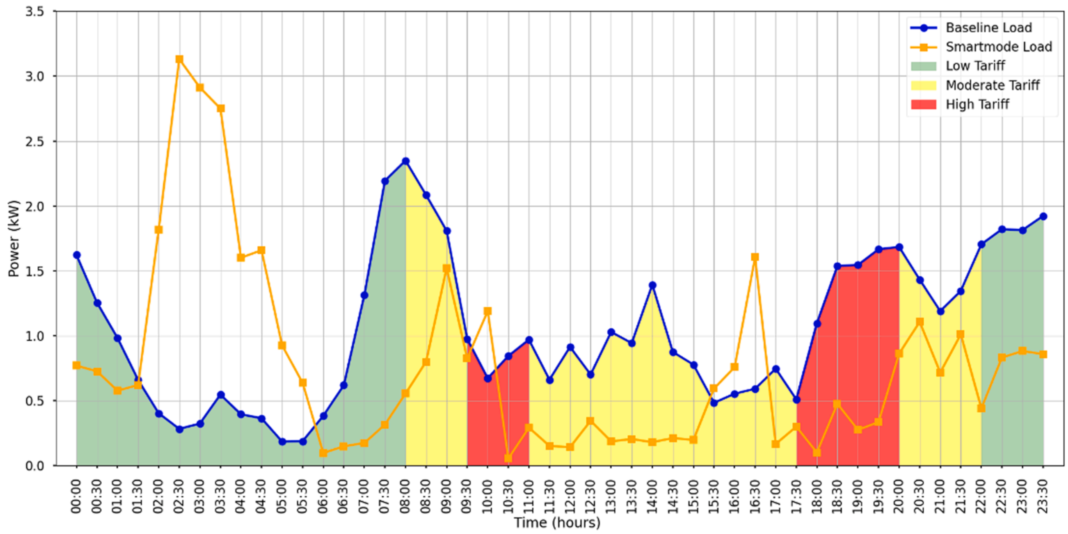

Fig. 13. Effects of load shifting due to the Klugit device.

an average of €0.754/day in the baseline and €0.4866/day in the smart mode to satisfy their heating demand. This results in a cost-saving of 35.54% for the consumer. The annual cost savings the consumer enjoys equate to €97.63 without affecting the thermal comfort of the consumer.

While operating in smart mode during the pilot project, one EWH used more electricity than the baseline operation, as shown in Fig. 14. In this case, the smart mode used an additional 0.05 kWh/day relative to the baseline operation. However, in this case, due to shifting the load from high tariff periods to lower tariff periods, the cost to the consumer was still lower when the smart mode was operating. In the baseline approach, this EWH had a daily cost of €0.33/day, while in the smart mode, the cost was reduced to €0.277/day. This result shows the benefit of load shifting and how it can directly benefit the consumer even if more electricity is used to satisfy heating demand in some instances.

Therefore, considerable savings can be observed when this smart plug is connected to an EWH and operating in smart mode. Importantly, as there were only 15 homes in the pilot project, there was constant communication between the users and the project organizers. This allowed the consumers to report any issues with the smart mode operation, such as inadequate hot water.

Therefore, considerable savings can be observed when this smart plug is connected to an EWH and operates in smart mode while maintaining consumer comfort. These savings in both energy and money are expected to increase with increasing numbers of installed devices. The savings are direct savings accrued to the consumer. A summary of these results is shown in Table 5.

4.2. Peak load reduction

The ability of the installed device to reduce energy consumption and shift load to periods of lower demand also has important benefits for the system operator, and this is especially true in the case of São Miguel

Table 5
Summary of results from the São Miguel pilot.

	Average energy saved	Average energy removed from high tariff period	Average energy added to low tariff period	Money saved by the customer
Azores Pilot	1.33 kWh	0.92 kWh	1.26 kWh	€0.267 /day
Annually	485.45 kWh	335.8 kWh	459.9 kWh	€97.63

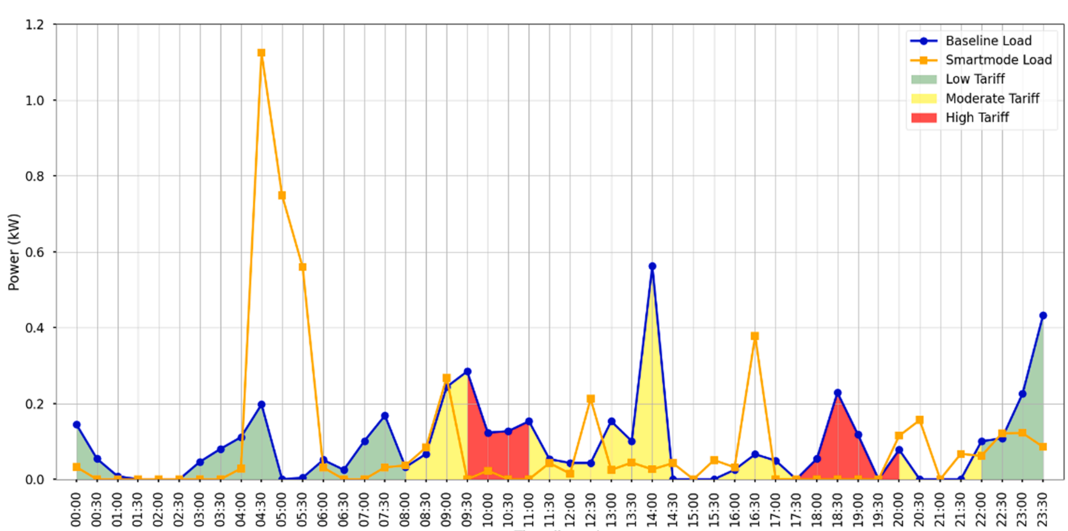

Fig. 14. Energy use of selected EWH with higher energy consumption in smart mode. for device 9.

Island. As mentioned, the island relies heavily on imported fossil fuel (diesel and oil) to run the main thermal power plant, the 98 MW capacity Caldeirão Thermoelectric Power Plant (CTCL). This plant uses a combination of diesel and fuel oil to generate electricity. Due to the fuel being imported for this plant, its generating costs are significantly higher than other resources in São Miguel. This is shown in.

Table 6, which contains the generating or operational costs of each technology for São Miguel and is provided by EDA.

In addition, the operating costs of the CTCL plant are dependent on numerous factors, including the global oil price. This can vary significantly. Between January and June 2021, the operational costs for the CTCL plant were €0.1241/kWh, but this can change depending on the global oil price, which has been very volatile in the past 12 months [14]. The dispatch order is the order in which the different technologies are used to meet the system's demand. It depends on numerous factors such as power plant composition, capacity, capital and operational costs, and flexibility (ramping, load following, frequency regulation). The dispatch order is essential in this analysis as a collection of installed devices can operate as a flexible resource and thus would be able to partially replace the peaking plants used by EDA to meet the demand. The collection of devices may function as a Virtual Power Plant and can respond to specific requests from the system operator. The devices were compared to the biogas and thermal plants, which are dispatch orders 4 and 5.

Figure 15 shows the average energy mix for São Miguel on 7 July 2021. It can be seen that both geothermal and hydro act as baseload generators. Biogas (yellow area) has the cheapest operational cost but does not contribute significantly to electricity generation (biogas only produced 0.17% of electricity in São Miguel in 2020) and only produces electricity when there is enough feedstock material. Wind generation has a relatively small contribution on this day, but it has a larger share in the late afternoon. The CTCL plant operates as a mid-merit plant to satisfy the remaining demand.The quantity of electricity generated by each technology and its associated generation costs are reflected in Table 7, and the data are provided by EDA [14]. These are the commercial costs paid for each unit of electricity the plants generate under the relevant production agreements. The amounts of energy generated by solar PV and biogas are estimates, as they are independently owned and operated. The amount of power generated by these two sources is not currently meaningful to the broader energy system of São Miguel.

On São Miguel island, there are 64 055 low-voltage clients. Of these clients, 8.3% already use an existing electric water heater (based on the "Inquérito ao consumo de energia no sector doméstico – 2020"); thus, this is the initial target market for the intelligent EWH. This provides a currently addressable market of 5317 EWHs in São Miguel. In the future, it is expected that an increasing number of low-voltage clients will switch from liquefied petroleum gas (LPG) boilers (currently, 88.3% of low-voltage clients in the Açores islands use LPG boilers to heat water) to electric water heaters.

Various scenarios were considered to investigate the system-wide impact of the devices. These initial scenarios were classified as low, medium, and high uptake scenarios depending on the percentage of clients with an existing EWH who will install a device. These scenarios are the following:

- Low uptake: Klugit devices are installed on 20% of existing EWHs (20% of 5317 EWHs gives 1063 devices).
- Medium uptake: Klugit devices are installed on 40% of existing EWHs (40% of 5317 EWHs gives 2127 devices).
- High uptake: Klugit devices are installed on 80% of existing EWHs (80% of 5317 EWHs gives 4254 devices).

Table 6
Dispatch order and operational costs.

Plant Type	Dispatch order	Rate (€/kWh)
Geothermal	1	0.101
Hydro	2	0.101
Wind	3	0.101
Biogas	4	0.0924
CTCL	5	0.1241

Fig. 16 below shows the total generation profile for São Miguel (pink curve) and a load of these EWHs operating both in smart mode (orange curve) and baseline mode (blue curve). For this analysis, the medium uptake scenario was considered. While the magnitude of the impact of the devices may be limited in this scenario, we can see an increase in the early morning load when the fleet of devices operates in smart mode. This impact is only expected to increase as the number of devices increases.

This shift in early morning load from the connected devices operating in smart mode is shown in Fig. 17. The pink line shows the existing generator load or standard load profile with passive EWHs, in other words, the current situation. The green lines would represent the load curve if the aggregated EWH operated in the smart mode in the different uptake scenarios. There is load shifting, especially with an increase in the load in the early morning when the devices are heating. Installing the devices can reduce the total energy used by 2831.98 kWh daily or 0.21% of total energy under the medium uptake scenario. This figure is solely from installing the device on existing EWH and is complementary to the other benefits mentioned earlier

4.3. Avoided emissions

Reducing energy use and associated operating costs are not the only benefit that this aggregated group of intelligent EWH may provide. Due to the high share of imported fossil fuels (both fuel oil and diesel) used by EDA to generate electricity throughout the Azores, the carbon intensity of the electricity is high, with a value of 421.5 gCO_2/kWh in 2020 [13], which is well above the average for Portugal which stands at 201 gCO_2/kWh [16]. This value highlights the importance of reducing emissions in the Azores islands, significantly reducing the amount of fuel oil imported. Because of the high carbon intensity of fuel oil, even though the absolute amount of energy saved using intelligent EWH is less than 1% of total energy, by reducing the electricity used, especially from the CTCL plant, the group of EWH can have a significant impact on the emissions profile of São Miguel. Through the analysis of the hourly generation and demand profiles, the amount of thermal generation displaced by the intelligent heating of the EWHs can be quantified.

Fig. 18 compares the thermal generation used for residential water heating in the passive (black) and smart modes (green) in the medium uptake scenario. This substitution leads to a reduction of 0.37% of thermal generation or 2831.98 kWh per day with a generation cost of €0.1241/kWh. This reduction in thermal generation varies between 1413.79kWh per day (0.1% of total generation from CTCL) in the low uptake scenario and 5657.8 kWh per day (0.32% of total generation from CTCL) when the high uptake scenario is considered. Solely based on the avoided generation from the CTCL plant, assuming a unit cost of a Klugit device of €85 per unit (this cost is obtained directly from Klugit Energy and considers the most up-to-date production cost), the costs to equip 2127 residential homes with the device will be repaid in 1.4 years, solely from not needing to use the CTCL plant to generate this extra electricity that is not required. Considering a margin of error of 15% for both an increase and decrease of the unit costs, this means that this set of Klugit units would repay their purchase price in 1.61 years in the case of higher costs or 1.22 years in the case of lower costs. This benefit is in addition to the direct cost-saving benefit to the consumer of nearly €100 annually based on reducing energy consumption.

Displacing this thermal generation will also have positive impacts on the emissions profile of EDA. Assuming that the aggregate group of intelligent EWH can replace 2831.98 kWh per day in the medium uptake scenario and using a carbon intensity of 670.729 gCO_2 /kWh for the thermal generation, leads to a reduction of 693.31 tons CO_2 per year

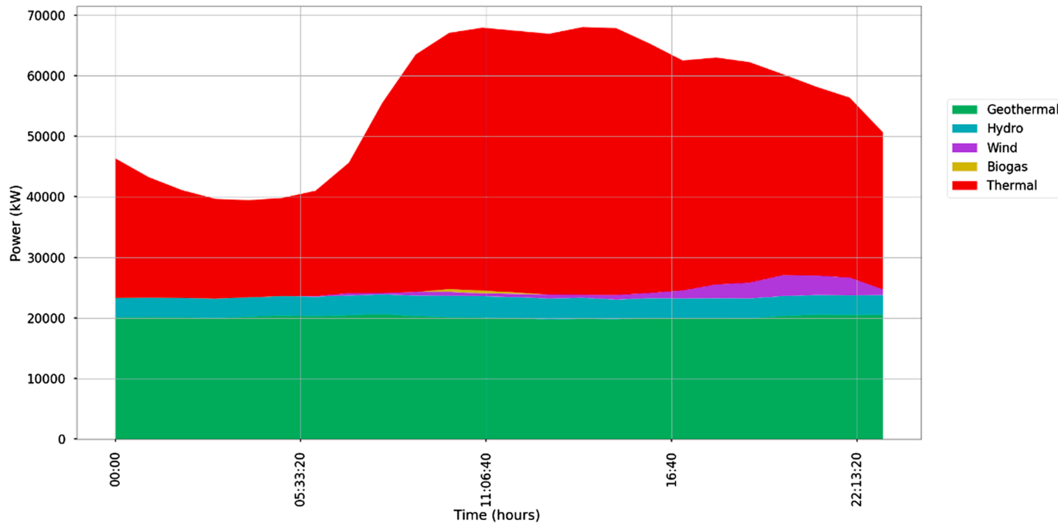

Fig. 15. Energy mix for 7 July 2021.

Table 7
Energy generated and costs for São Miguel in 2020.

Technology	Energy generated in 2020 (MWh)	Operational cost (€/kWh)
Thermal (CTCL)	218673.81	0. 1241
Geothermal	169447.68	0.1011
Wind	15028.81	0.1011
Hydropower	23846.95	0.1011
Solar PV	21	0.1011
Biogas	700	0.0924

(346 tons CO_2 in the low uptake scenario or 1385.4 tons CO_2 in the high uptake scenario) emissions from thermal generation by simply plugging in one of these devices to manage the heating load of an EWH efficiently.

EDA emitted 368 000 tons of CO_2 in 2020; therefore, aggregated devices can reduce this total by 0.18 % by only installing 2127 of these devices across São Miguel (this corresponds to 0.089 % in the low uptake scenario or 0.36 % in the high uptake scenario). This substitution can have important implications for reducing CO_2 emissions and improving air quality.

4.4. Impact on the physical infrastructure

Another possible benefit that intelligent EWH may offer the system operator is the reduced load placed upon the physical infrastructure, such as transformer units in low-voltage networks. These EWH and other distributed energy resources may operate as non-wires alternatives to investing in physical infrastructure upgrades [11]. The information on a substation transformer data from the region in São Miguel, whose data was available, is gathered and used for the analysis. The daily transformer load profile of the substation is shown in Fig. 19. The total transformer load is pink, while the baseline, passive EWH demand is blue. While the lines are nearly identical, there is a slight decrease in the energy used during the two peaks, at around noon and again at 20:00. There is also an increase in the demand during the early hours of the morning at around 03:00. The intelligent EWH operation is shown in orange under the medium uptake scenario. The straight horizontal lines represent the mean load for the different loads over the entire day.

Fig. 20 shows the baseline transformer load in pink (Transformer Load). The green line is created by removing the baseline EWH load and replacing it with the intelligent load from the devices. There is load shifting occurring when the smart EWHs are operational. However, there is no peak reduction occurring. The peak load is slightly increased,

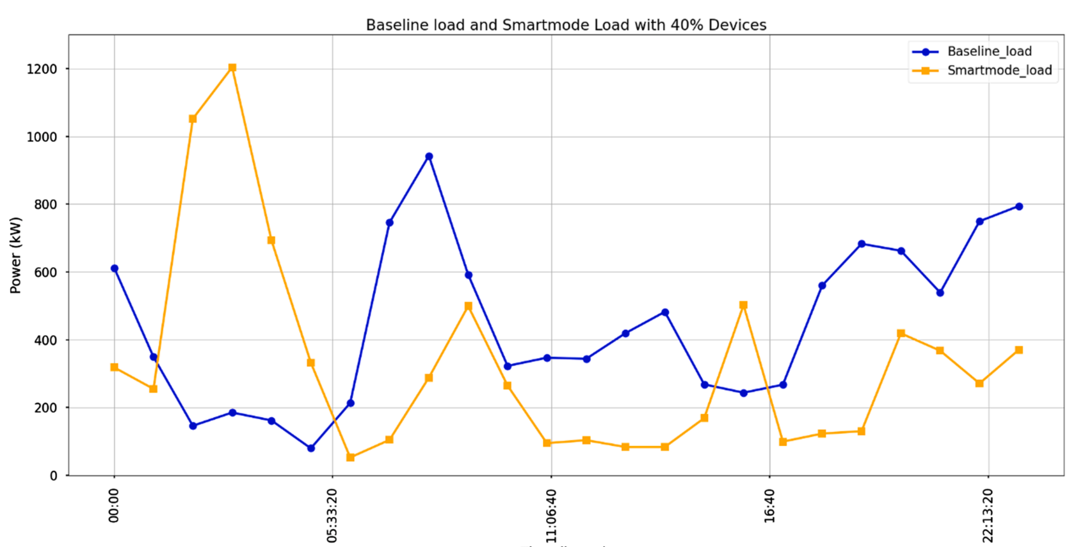

Fig. 16. Total load compared to baseline and smart mode demand of fleet of Klugit devices.

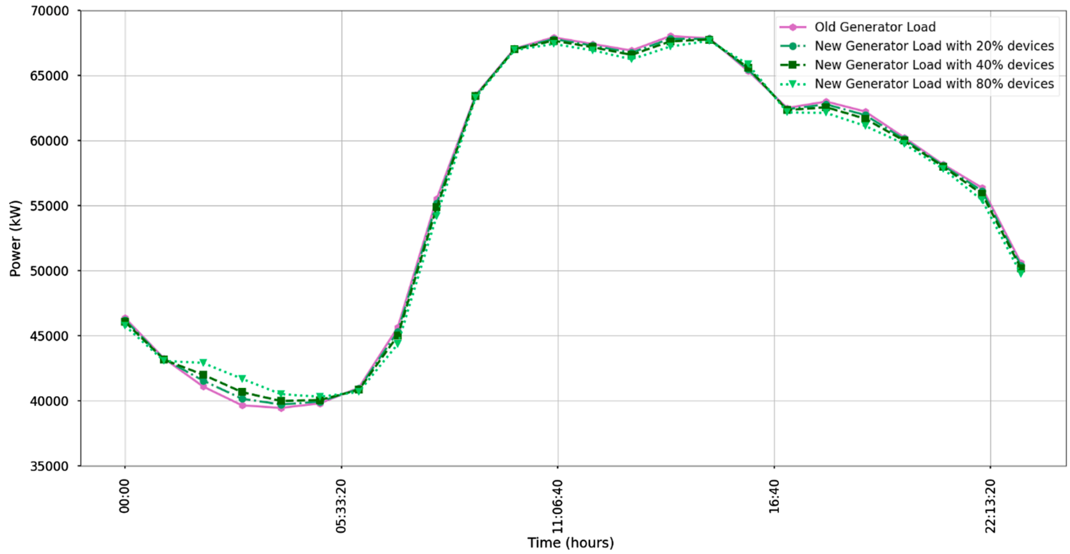

Fig. 17. Baseline load vs. smart mode load.

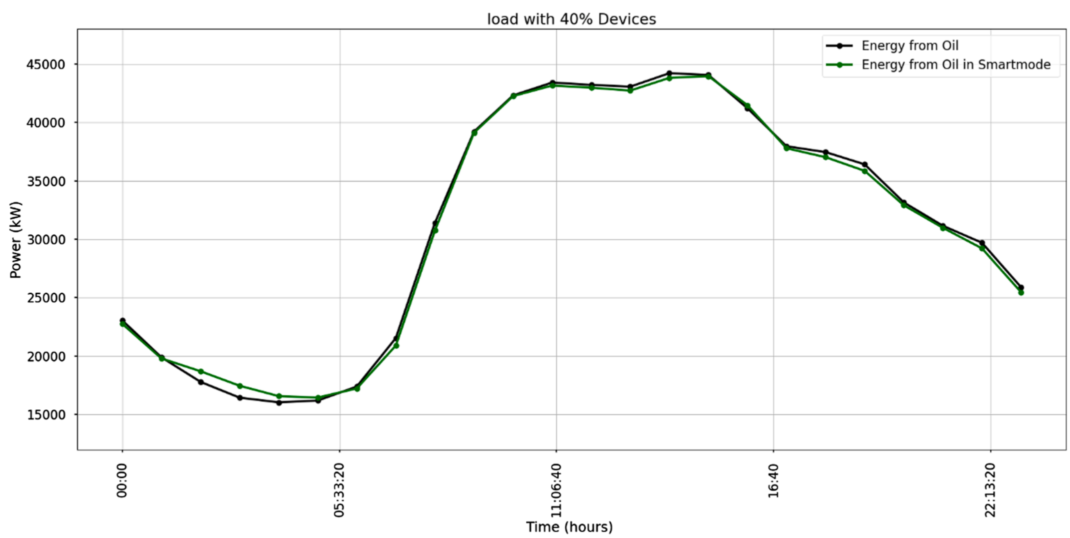

Fig. 18. Energy from thermal generation from CTCL in the baseline and smart modes.

and the minimum load is reduced. However, the objective of this device is not currently related to minimizing the impact on the physical infrastructure.

A figure showing the differences in power demanded in the baseline (Old transformer load in pink) and smart mode for different penetration levels (shown in green) of the device is shown in Fig. 20. However, there is minimal peak reduction occurring. The peak load is slightly decreased, and the minimum load increases, especially at a penetration level of 80%. These results are small as the objective of this device is not currently related to minimizing the impact on the physical infrastructure.

The objective is to reduce the cost of satisfying the consumers' hot water demand. Therefore, in the future, the objective may be modified so that reducing the impact on the physical infrastructure is considered. This objective can be achieved by allowing the utility to control the EWH during high system stress. This control is possible as the simple device transforms a passive EWH into a controllable distributed energy resource asset that can be used to satisfy several objectives from different agents.

4.5. Results from the customer satisfaction survey

At the end of the pilot project, consumer semi-structured interviews, surveys, and questionnaires were also carried out to measure consumer satisfaction with the devices installed qualitatively.

The quantitative survey consists of 20 questions, of which 18 were categorical questions about recommendations, application features, design, installation, and usability on a scale from 1 to 10. We have one multiple-choice question with five.

different prices and a section for consumer suggestions for improvement. The consumers gave the device a global average score of 7/10. The following list contains the key areas of focus in the questionnaire:

- Recommendation: how probable they would recommend the device to a family or friend.
- App features (with eight questions): measuring the actual satisfaction with the device's features themselves, and seven others measuring the importance of the following list of characteristics:
  1. The priority given to the "low peak" period and avoiding the "high peak" period to heat water.

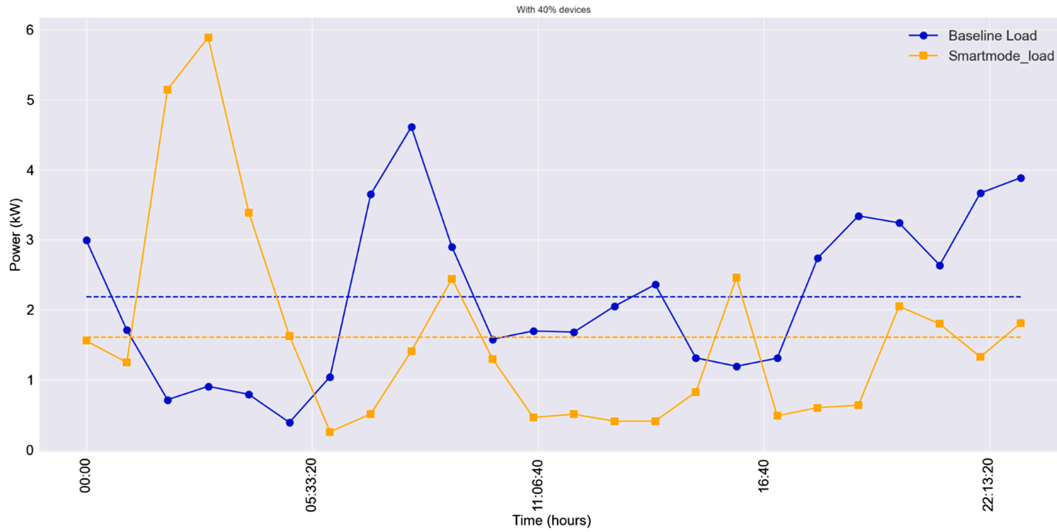

Fig. 19. Transformer load with baseline and smart mode loads.

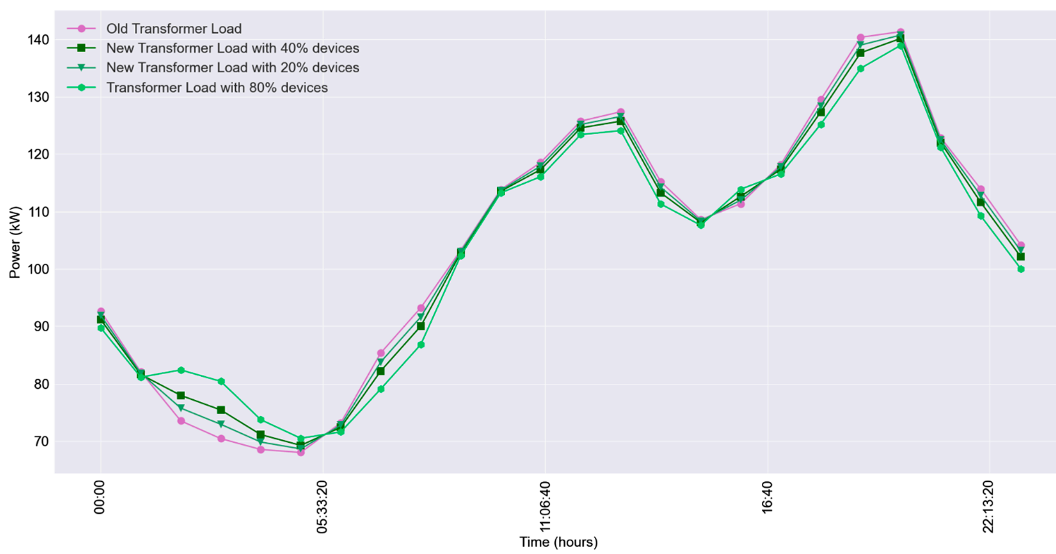

Fig. 20. New (smart mode) and old (baseline) transformer load.

2. Reduction of thermal losses from the water heater.
3. Viewing savings in the app.
4. Visualization of the reduction of CO2 emissions.
5. Visualization of the forecast for upcoming hot water needs.
6. Request additional hot water when needed (Heat Now) in the app.
7. Turn off smart mode when needed.

- Design: consisting of 3 questions measuring satisfaction on the following topics:

1. Design and user experience of the mobile app.
2. The appearance of the product.
3. Packaging.

- Installation process: assessing the level of satisfaction during the experience of the device installations.
- Usability: 3 questions measuring satisfaction, safety, trust, and feeling:
  1. Satisfaction with the ease of use.
  2. Degree of safety and trust when using the device.
  3. The feeling of owning one of the devices.

From a qualitative perspective, an interview script was prepared with 14 groups of small open-ended questions with 10 participants. Each participant was asked the same group of questions individually via remote, semi-structured interviews. The interview discussed the installation process, the existence of other water heaters, the previous use of different devices to control energy consumption (for example, timers), the difference between Klugit and those devices, lack of hot water during the test period, satisfaction, the use of the app and the 'heat now' feature, changes on the bill, feelings about savings presented on the app and overall services, and finally the probability of recommendation for the device and services.

Results from the survey indicate that the consumers' DHW demand was met during the pilot project. Four users gave the device a 10/10 score in the user satisfaction and recommendation category, while only two scored under 5/10, so the median score was 8/10. Regarding the ease of installation, only two users scored under 7/10, and the median value was again 8/10. There was an average of 7.3/10 for ease of use of the device (median value of 8/10) and 6.1/10 for satisfaction with the functionality of the device, with a median value of 7/10. The average rating for the satisfaction of the mobile application was 7/10, with a median of 8/10. Regarding the aesthetics and packaging of the product, the average score was 7.3/10 (median 8/10) and 7.6/10 (10/10), respectively. The functionalities of the device that the consumer valued as most important and would like to be included in future versions are as follows (ranked from the most important to the least important).

1. Load shifting or avoiding high tariff periods.
2. Reducing the contracted power by ensuring that the EWH is not operating simultaneously with other major appliances.
3. The ability to disconnect the smart mode or use the ‘heat now’ function when necessary.
4. The sustainability and design of the device and the packaging.
5. The ability to visualize savings from the smart mode in the mobile application.
6. Viewing the forecasted schedule for hot water demand.
7. Reducing the thermal losses from the EWH.
8. Reducing CO2 emissions from the energy used to heat the EWH.

The consumers stated that the device installation was quick, easy, and straightforward. Several consumers were already using a programmable plug for their EWH, which might have simplified the installation process. Concerning the two users who were not completely satisfied with the device, the significant reasons were not related to the device. In one case, a weak Wi-Fi signal made communication difficult between the device and the home router. In the other case, the consumer was required to use hot water during peak periods, and the device was specifically designed to avoid use during peak periods. The consumers stated that the major reason for using the mobile application was to utilize the ‘heat now’ functionality and then to view the estimated savings from the smart mode and the forecasted schedules for hot water demand.

In terms of areas identified for further improvement, the survey and questionnaire identified the following:

- Improve the device’s WIFI connectivity.
- Modify the system to allow for heating during high tariff periods if necessary to meet the DHW needs of the consumer.
- Once enough data has been gathered, modify the device to act more like a standard programmable plug. Propose a heating schedule to the consumer and request approval of this schedule. The schedule will not be changed unless directed by the consumer. Suggestions for improvement will be sent to the user but will require their approval before application. This will allow the user to become more familiar with the heating patterns of the EWH. This will help users regarding the optimal periods of EWH operation, especially those customers who already have a standard programmable plug, as was the case in several of the users in the Azores pilot study.
- Improve the feedback given to the consumers, especially around their savings in the electricity bill. Accurate and up-to-date savings can act as positive reinforcement for consumers.
- Add an option to switch the application to Portuguese (and other languages in the future) to improve ease of use.

5. Discussion and conclusions

This section discusses the results presented in the previous section and draws conclusions from these results.

5.1. Discussion

This paper has discussed the innovative development, implementation, and validation of a device to convert a passive EWH into an intelligent, controllable, distributed energy resource. The device uses machine learning techniques to accurately forecast DHW demand based solely on the data received from a clip-on temperature sensor. This paper contains the details of an actual case study in collaboration with EDA utility on the island of São Miguel, Portugal. The pilot project showed that these devices function very well and are highly effective in controlling water heating to benefit both the consumers and the system operator. Benefits accrued to the consumer regarding reduced energy costs, and to the electrical utility, mainly through avoided generation. These benefits show the potential for new devices and optimized interactions with the electricity network. These devices or non-wires alternatives may usher in a new paradigm of active residential demand and improved ability to respond to requests from the network operator. These benefits are even more critical in small island systems which rely heavily on renewable energy sources, especially in the current era of uncertain costs for imported fossil fuels.

The paper also showed that the device was well received by the participants, being easy to install and operate. Overall, the qualitative results showed that the device did not significantly affect the consumer’s comfort while saving them a considerable amount of their monthly heating bill. The consumers enjoyed the sense of control of their EWH and their ability to visualize their estimated savings and forecasted hot water demand. Importantly, this shows that consumers can be incentivized to actively participate in the energy system using a combination of cost-saving measures, innovative applications of machine learning techniques, and forward-looking initiatives from electrical utilities, as was shown in this case by EDA being an active participant in the pilot project.

5.2. Conclusions

In terms of direct benefits to the consumer, the device reduced the energy used to heat water by an average of 1.33 kWh per day per device, or 26.43% throughout the pilot study, which is significant. This energy reduction led to an estimated average saving of 35.5% per consumer. The annual cost savings the consumer enjoys equate to €97.63 without affecting the thermal comfort of the consumer, which is noteworthy. This monetary benefit exceeds the unit price of the device (estimated at €85 per unit), and with a lifetime of 5 years, the device can bring significant financial benefits to the consumers while maintaining their comfort. The device can also provide direct and indirect benefits to the system operator. Using a group of these devices in a coordinated manner, similar to a Virtual Power Plant, the devices can reduce the system’s peak load, increase load during low-demand periods, and displace electricity generated by fossil fuels. Using a fleet of 2127 intelligent EWHs, it is estimated that the devices can reduce total energy used on São Miguel by 2832 kWh per day just through the efficient heating of water, with no noticeable impacts on the thermal comfort of the consumer. The energy savings from these devices in displacing generation from the CTCL plant ensured that the devices had an acceptable payback period. Additionally, it is estimated that these devices can reduce the carbon emissions of EDA by 693.31 tons CO_2/year. Further, the costs of importing fossil fuels to the islands will be reduced.

There are some limitations identified from the model development and pilot project process. These limitations include that the consumers were employees of EDA and volunteered for this project. The volunteers’ background could mean they are more familiar with the technology. A more diverse sample of people should be recruited for the following projects.

The model optimized the system without feedback from the consumer. In the future, the user could suggest changes to initial heating patterns to integrate the consumer’s behavior better. The model was focused on minimizing the cost of a single consumer. There was no attempt to pursue additional goals such as aggregated peak load reduction or displacing fossil fuel-based generation. These objectives can be included in future iterations of the model, and a multi-objective process can be followed depending on the consumer’s preferences.

Future directions can include translating the application into different languages and improving the vibration sensor for improved water flow forecasting. This includes investigating other locations of the vibration sensor to ensure that the data obtained is as accurate as possible. Additionally, different locations and environments should be tested to ensure that the device works in various settings. In addition, the device's ability to participate in real-time demand response programs and provide ancillary services such as network frequency regulation.

In closing, this paper has shown that a relatively cheap and user-friendly device to intelligently control an electric water heater can bring significant benefits to both consumers and the system operator. These benefits included energy savings, peak load reduction, and reduced emissions through avoided generation. This paper provided evidence of a successful pilot project where this innovative device was used by actual consumers for six months and offered real cost savings to the households while maintaining their thermal comfort.

CRediT authorship contribution statement

Matthew Gough: Conceptualization, Methodology, Investigation, Writing – original draft. **Kush Rakhsia:** Investigation, Data curation, Writing – original draft. **Tiago Bandeira:** Conceptualization, Project administration, Writing – original draft. **Hugo Amaro:** Methodology, Validation, Writing – review & editing. **Rui Castro:** Writing – review & editing, Supervision. **João P.S. Catalão:** Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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