**Report on the Klugit Energy and EDA pilot project on São Miguel using intelligent electric water heaters**

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# Executive summary

This report presents the details and findings of the Klugit Energy residential pilot project carried out on the island of São Miguel with the cooperation of Electricidade Dos Açores, S.A. (EDA). This report covers the results for six months from July to December 2021. The objective of the pilot project was to examine the ability of the Klugit device to intelligently heat water in the EWH according to the residential hot water demand using non-intrusive sensors and machine learning techniques. This intelligent heating has the potential to reduce the energy bill of the consumer by avoiding high tariff periods and reducing unnecessary heating which reduces the energy consumed and thus reducing both the bill and potential emissions associated with electricity generation in São Miguel.

Due to its characteristics, São Miguel is very dependent on thermal generation using fossil fuels. This dependence on imported fuels is due to various factors such as energy security, stability, quality of supply, and available and cost-effective means of production. 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 from the Estratégia Açoriana para a Energia 2030 (2030 Energy Strategy for the Azores) published by the Regional Directorate of Energy of the Açores. The intelligent electrification of residential water heating can displace the use of fossil fuels, especially if heating of the water takes place during periods of high renewable energy generation.

Considering the context of the Azorean power system and examining past literature in this field, the main objectives of the pilot project were to design, validate and implement a non-intrusive device to intelligently control electric water heaters in an easy and user-friendly manner. In addition, a machine-learning algorithm was developed to predict residential hot water consumption. 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 in a cost-efficient manner. The device was used in such a way as to not impact consumer comfort during the pilot and this was verified through a consumer survey and questionnaire at the end of the pilot project.

Results show the impact of the device on consumer costs and avoided emissions. Additionally, the benefits provided by the device to the electrical utility in terms of avoided costs of generation are shown. In terms of direct cost savings to the consumer, the across the 10 installations in the pilot, the device reduced energy use by an average of 1.33 kWh/day per consumer which represented an average reduction in heating demand of 26.43%. Combining the effects of reducing energy consumption and switching heating load from high tariff periods to low tariff periods, the smart mode operation reduces the energy cost to consumers. Based on the tariffs in place in this pilot project, consumers would receive an average cost-saving of 35.5% on their domestic water heating costs~~.~~ This equates to an average annual cost savings of €97.63 without affecting the thermal comfort of the consumer. This value is above the price of the Klugit device.

Aggregating a group of Klugit devices across São Miguel can provide both load shifting and energy efficiency benefits to the system. Calculations show that a fleet of 2127 Klugit devices can reduce the total energy used by 2832 kWh per day or 0.21% of total daily energy. A large amount of this energy savings is achieved by reducing thermal generation which also has the benefit of reducing greenhouse gas emissions. Results indicate that this fleet of Klugit devices can reduce total thermal generation by 0.37% and this leads to a reduction of 693.31 tons of CO2 per year in the emissions from thermal generation by simply utilising a Klugit device to manage the heating load of an EWH efficiently. The report also shows that the device was well received by the participants in the pilot study and that it was easy to install and operate. The qualitative results show that the device did not significantly affect the consumer’s comfort. The consumers enjoyed the sense of control of their EWH and their ability to visualise their estimated savings and forecasted hot water demand.

In summary, this report has shown a simple and cheap 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 which are all especially important in island power systems such as São Miguel.

# Introduction

This report presents the details of the ongoing pilot project between Klugit Energy and Electricidade Dos Açores, S.A. (EDA) in São Miguel concerning the implementation of several smart Klugit devices and their impact on the operation of residential electric water heaters (EWHs). The objective of the pilot project was to examine the ability of the Klugit device to intelligently heat water in the EWH according to the residential hot water demand using non-intrusive sensors and machine learning techniques. This intelligent heating has the potential to reduce the energy bill of the consumer by avoiding high tariff periods and reducing unnecessary heating which reduces the energy consumed and thus reducing both the bill and potential emissions associated with electricity generation in São Miguel.

The increasing ability of previously passive residential loads, especially electric water heaters, to become actively participate in the energy management system brings several benefits to several actors within the system. The identification and quantification of these benefits is the main research question of this study. Broadly speaking these benefits can be allocated either upstream of the device or downstream. Upstream benefits of these intelligent devices are accrued by various parties such as distribution system operators (DSOs), energy retailers and eventually aggregators or virtual power plant operators. The downstream benefits accrue to the device owner.

Upstream benefits can include reduced peak load through load shifting. This can lead to less energy being demanded at peak periods and intelligent loads during low demand periods which can also reduce the need for physical network infrastructure upgrades and an improved peak to average ratio. The electrification of heating can lead to increased demand for electricity and so better integration of renewable energy. Typically, electricity produced at peak periods is generated by more expensive peaker plants therefore, the reduction of peak load can have outsized benefits in terms of cost reductions. This is especially relevant for the power systems of islands, as is the case in this report. 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 island promoting energy security.

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 gas water heaters which intelligent electric water heaters can even increase access to clean and affordable energy services.

This increased ability to intelligently control previously passive loads is being driven by many factors, including increased automation 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 diverse devices to work together to meet various load demands in an automated and intelligent manner helping usher in the clean energy transition.

The Klugit device harnesses this newfound ability to intelligently control residential EWHs and provide benefits to both the consumer and the wider grid all the while ensuring that the consumer’s desire for hot water is maintained.

## Motivation

### Azorean Power System

The Autonomous Region of the Azores is composed of nine islands that are widely dispersed and differ significantly in size. Thus, they are classified as isolated microsystems with no electrical connection between the islands. The nine islands utilize a wide variety of different electricity generating technologies depending on the endogenous resources and the demand on each island. Due to their characteristics, these islands are generally very dependent on thermal generation using fossil fuels. This dependence on imported fuels is due to various factors such as energy security, stability, quality of supply, and available and cost-effective means of production (Silva and Estanqueiro, 2020). Each island has a main fossil-fuel based generator which typically uses a diesel engine similar to those found on ships as these engines tend to be reliable. 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 from the 2030 Energy Strategy (EAE 2030) for the Azores published by the Regional Directorate of Energy of the Açores (Melo Carreiro et al., 2020).

Currently, the most widely used renewable energy source in the Azores is geothermal energy although it is only being exploited on two of the islands, namely 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 of the islands except for Corvo. Hydropower is the next most developed source of renewable energy although it has the longest history of development in the archipelago (Electricidade dos Açores, 2020).

The focus of this pilot study was on the island of São Miguel and thus, a more in-depth discussion of its electricity mix is provided. As of 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 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, there was 422.15 GWh of electricity delivered to the grid in São Miguel. Roughly 50% of this was from the thermal power plant, 40% from the geothermal plants, 6% from the various hydroelectric plants and 4% from the wind farm.

### Klugit Energy

A Klugit device is installed to convert a passive electric water heater into an intelligent device. This device consists of two components. The first component is a smart wifi enabled plug which plugs into a regular wall power socket and the EWH is plugged into the other side and the second component is a connected water use detection sensor that clips onto the hot water outlet pipe of the EWH. Therefore, this device is easily installed and required no technical knowledge, extra tools or modifications to the EWH unit. An example of an installed Klugit device is shown in the Figure below where the smart plug and the clip-on water use detection sensor are easily visible. The Klugit device has been under development since 2018 as a spin-off from Bosch. The prototypes were installed in 2020 and the first small-scale pilot project was carried out in conjunction with E-REDES, the Portuguese Distribution system operator, 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 (Tavares et al., 2021). The device reduced 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 Electricidade Dos Açores, S.A. (EDA) to commence in July 2021. EDA is the system operator operating the various electrical networks within the Autonomous Region of the Azores.

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## Literature Review

The idea of operating electric water heaters intelligently to provide benefits to both the distribution operator and the consumer has been examined before (Pereira et al., 2020). However, these previous studies tend to rely on intrusive monitoring techniques for water temperature, do not update the operation and control strategy of the EWH depending on the consumer’s hot water usage and finally, these studies do not validate and implement their models in a real-world pilot program setting.

The potential of EWHs to provide benefits to either the consumer or the DSO has been the subject of significant research in the past years. For example, the authors (Shen et al., 2021) develop a data-driven optimization model for the smart scheduling of EWHs to meet several demand-side management requests. The authors utilise model predictive control to develop a two-state EWH model and test it on real-world data consisting of 77 EWH 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 are 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 were not considered.

A study that did investigate results from a real-world pilot project considering the demand response flexibility from smart appliances, including electric water heaters, is (D’hulst et al., 2015). The study was based on the LINEAR project which examined residential demand response in the Flanders region of Belgium. The project prioritised user comfort over other technical objectives. The paper considered data from 15 residential EWHs among other appliances. The developed system needs to be attached directly to the EWH and is not controllable by the consumer as is the case in the Klugit device.

A study that focused on the benefits provided by intelligent EWH to the grid was conducted by (Clarke et al., 2020). The authors used virtual devices to emulate real-world EWHs. A thermal model was used for the estimation of 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 services as well as 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 were not considered in this study.

The ability of EWHs to modify residential electricity consumption due to external incentives was investigated by (Shah et al., 2016). The paper used a simplified EWH model and used 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 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 comfort of the consumer were not considered.

The paper authored by (Tejero-Gómez and Bayod-Rújula, 2021) demonstrates and validate a simple and low-cost control module for the intelligent operation of an EWH. The authors use this system to minimise the cost of water heating in the home while respecting the user’s comfort. Unfortunately, the system relies 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 reduced significantly while maintaining the user’s comfort levels.

Another model which uses a heuristic algorithm to optimally schedule EWH under a dynamic pricing tariff is presented by (Kapsalis et al., 2018). The papers discuss above show that the concept of intelligent electric water heaters has been studied in the past. However, several shortcomings of these previous studies have been highlighted and Table 1 shows how the Klugit device and the pilot project address those shortcomings through several novel contributions.

*Table 1: Relevant existing literature*

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Paper** | **Type of control** | **Consumer cost** | **Peak load** | **Pilot project** | **Non-intrusive** | **Consumer comfort** | **Data set used** | **Emissions considered** |
| Shen et al., 202 | Model predictive control | Yes | No | No | Not applicable | No | Data set of 77 EWH for 120 days | No |
| D’hulst et al., 2015 | Linear programming | Not considered | Yes | Yes | Yes | Yes | 15 residential EWH | No |
| (Clarke et al., 2020 | Unspecified thermal model | No | Yes | No | Not applicable | No | Synthetic data | No |
| Shah et al., 2016) | Greedy algorithm | Yes | Yes | No | Not applicable | No | 450 apartments for 14 months | No |
| Tejero-Gómez and Bayod-Rújula, 2021 | Heuristic | Yes | Yes | Yes | No | Yes | Actual data from single EWH | No |
| Kapsalis et al., 2018 | Heuristic | Yes | No | No | No | Yes | Authors own | No |
| This project | Machine learning algorithms (XGBoost, LSTM) | Yes | Yes | Yes | Yes | Yes | Actual data from a pilot project | Yes |

## Main Contributions

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

* Design, validation and implementation of a non-intrusive device to intelligently control electric water heaters in an easy and user-friendly manner.
* Development of a machine-learning algorithm to predict residential hot water consumption. 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 in a cost-efficient manner.
* Details and results of a pilot study where the device was implemented in 15 homes on the São Miguel island for a period from July to December 2021.
* Evidence that the comfort of the consumer was not impacted during the pilot through a survey conducted on the pilot study homes. This introduces important qualitative information relating to the preferences, behaviour and comfort of the subjects.
* Quantification of the results shows the impact of the device on consumer costs and avoided emissions. Additionally, the benefits provided by the device to the electrical utility in terms of avoided costs of generation are shown

## Report Organization

The rest of the report is structured as follows: Section 2 contains the details of the methodology followed during the design and application of the machine learning-based control algorithm. The experimental validation of the algorithm and device are also included in this section. Section 3 presents the information related to the pilot project conducted on the São Miguel island within the Açores archipelago. The results of the case study are presented in Section 4. Finally, Section 5 contains the conclusions drawn from these results.

# 2- Methodology

This section introduces the methodology used by Klugit during the pilot project. 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 presented.

There was a sequential methodology followed during the implementation of the device. The key parameter to identify was the 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, there was minimal data related to the DHW demand available to be included in the prediction model. As a result, the methodology was split into three distinct periods depending on the amount of data available for the prediction model. Each period used a different technique to forecast the hot water demand of each household. These techniques included simple regression, XGBoost, and finally Long-Short-Term-Memory (LSTM) networks.

## Theoretical background

### XGBoost

Once sufficient data was collected for the household from the clip-on vibration sensor, the Extreme Gradient Boosting (XGBoost) algorithm was used to predict hot water consumption. This was done to ensure more accurate and robust predictions. XGBoost is a widely used tree boosting system (Chen and Guestrin, 2016). 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 which has been successfully deployed in many real-world applications. The python interface of XGBoost was used in this paper (“Python Package Introduction — xgboost 1.5.2 documentation,” 2022).

The XGBoost algorithm is based on several decision trees with each tree being generated through a gradient descent method. The objective of the algorithm is to minimize a certain objective function (what is our objective function) which is subject to a second-order Taylor expansion. To reduce overfitting, the XGBoost utilises the complexity function of the tree to represent the objective function’s constant term. The mathematical formulation of the XGBoost algorithm is shown below:

*Equation 1*

*Equation 2*

*Equation 3*

In the equations above, represents a constant, represents the input vector, the number of leaves in the tree is shown by The chosen hyperparameters are represented by and . The actual value of hot water demand is shown by while the predicted value of hot water demand is shown by . The square loss function is represented by and the regression tree is represented by . Using the Taylor expansion, we can approximate the by the following:

*Equation 4*

Where and represent the coefficients of the first and quadratic terms of the Taylor expansion respectively.

### LSTM

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 predictive accuracy of the LSTM model (Hochreiter and Schmidhuber, 1997). Despite the increase in the predictive ability, this algorithm also required a larger amount of data for training and testing, hence the decision to first use the XGBoost model until such time that sufficient data was available. In this pilot project, 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 (Sak et al., 2014). 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.

Diagram, schematic

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*Figure 1: Structure of vanilla LSTM model (Van Houdt et al., 2020)*

Conceptually, an LSTM model is composed of a number of processing blocks and inputs. The interaction between these components is discussed below in Figure 1. The initial step is a block input that uses the output of the previous LSTM unit and the current input. This is expressed as

*Equation 5*

In the above equation, and are weights associated with and respectively and the bias weight vector is denoted as

The next step is to update the input gate which combines the current input x and the previous LSTM unity-1 with the cell value c from the previous iteration. This is shown in Equation 6.

*Equation 6*

With and are weights associated with , and respectively. The bias weight vector is represented by . The LSTM layer determines how much information is retained in the cell states from the previous steps. This layer also considers the selection of the candidate values, which may be added to the cell states as well as the input gate activation values, .

The next important aspect of the LSTM cell is the forget gate in which a decision about how much information to remove from the previous cell state, , is removed. In this step, the activation values, , of the forget gates are calculated using the current input, , outputs from the previous time step, , and the previous memory cell state, , the peephole connection and the terms representing the bias, . This is shown as:

*Equation 7*

With , , and are weights associated with , and respectively and the bias weight vector is denoted as .

The next step is to compute the cell value. This step uses the outputs of the block input, , the input gate, , and the forget gate, as well as the previous cell value. This is represented as:

*Equation 8*

The next output to be calculated is the output gate which combines the current input, , the result of the last LSTM unit, as well as the cell value, . Visually, this is represented by:

*Equation 9*

With , , and are weights associated with , and respectively and the bias weight vector is denoted as .

The final step is the calculate the block output. This is a combination between the current cell value and the current output gate. This is represented by:

*Equation 10*

## Implementation

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. This was used to train the temperature to flow converter model.

### 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, outputting a result of either 1 or 0 for a defining moment. The flow and processing of data in this model are shown in Figure 2.

Diagram

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*Figure 2: Pipeline for the temperature to flow converter model.*

The selected sampling rate was two minutes. The issue of whether the ratio between the sampled flow  
duration and real flow duration were significantly different in the predicted and real 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 aforementioned ratio. 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.

*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 | - |
|  | ReLU | - |
| 2 | 1D Convolutional | Filters: 64, Kernel size: 3 |
|  | Batch normalization | - |
|  | ReLU | - |
| 3 | 1D Convolutional | Filters: 64, Kernel size: 3 |
|  | Batch normalization | - |
|  | ReLU | - |
| 4 | 1D Global average pooling | - |
| 5 | Dense | Neurons: 2, Activation: softmax |

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 penalise 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.

The performance of various iterations of this model with these and different parameters was  
tested using the F-Score for the test set. A pseudo-grid-search was performed, using different  
values for all aforementioned parameters and testing the final F-Score for each. The best  
the model obtained an F-Score of 0.77 and was saved to be used in the relevant hot water usage  
prediction model as shown in Figure 3.

### Relevant hot water usages prediction model

This model predicts the relevant water usage for a set of days provided by the user. It is mainly  
used to make predictions about when water needs to be heated. The structure of the hot water prediction model is shown in Figure 4.

Diagram

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*Figure 3: Pipeline for training the relevant hot water usage prediction model.*

Diagram

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*Figure 4: Pipeline for obtaining the predicted relevant hot water usages for a set of the day*

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. It approximately identifies which hours were relevant hot water usages were seen in the last few weeks by using a Mean Shift model. The XGBoost model minimises 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 is composed 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 normalised before it is used as input into the network. The data is rescaled afterwards to reconstruct the temperature data. This approach was not appropriate for the flow data, as it is binary and so an activation function that allowed some progression, such as the softsign was necessary. Both temperature and flow versions were optimised by the Adam optimizer.

The Adam optimizer is an alternative to classical stochastic optimisation in deep learning problems. It combines the advantages of two other extensions of stochastic gradient descent. These other two extensions are the Adaptive Gradient Algorithm (AdaGrad) and the Root Mean Square Propagation (RMSProp) (Ruder, 2017). Further details of the Adam algorithm can be found in (Kingma and Ba, 2017) but in summary, the Adam algorithm achieves good results quickly and emerged as an excellent overall choice of algorithm for deep learning applications (Ruder, 2017). 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 the application of 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 afterwards, 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 and in this model, the duration of the flow can also be forecasted. The performance of the flow model was compared to the performance of the temperature model. For this comparison, the ratio of the correct predictions against the correct predictions plus incorrect predictions was used for all periods where water flow was predicted. The following two figures, Figure 5 and Figure 6 show the results of this comparison for the XGBoost and LSTM methods respectively. It can be seen that 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 water used which can be reported to the consumers to increase their knowledge of their 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 results of the model.

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*Figure 5: Comparison between the performance of the final XGBoost flow model versus the final XGBoost temperature model*

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*Figure 6: Comparison between the performance of the final LSTM flow model versus the final LSTM temperature model*

### System architecture

The models introduced above were incorporated into a larger digital infrastructure. This infrastructure allowed the Klugit 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 Figure 7. The relevant services and applications are shown with the flow of the information shown via the black arrows.

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*Figure 7: Infrastructure layout of the Klugit system*

# 3. Case Study

This section contains the details of the pilot project implemented in São Miguel carried out between July and December 2021. Klugit devices were installed in 15 homes and a photo of a typical installation is shown in Figure 8 below. The types of homes and equipment installed varied widely across the homes. The number of inhabitants ranged from two to five people in the home while the capacity of the EWH ranged from 80 l to 150 l. A standard installation and training process was done for each household. The Klugit device was controlled by a smartphone app, this allowed the users to monitor the hot water usage and also included a ‘heat now’ option. A screenshot from the app is shown in Figure 9. This option allowed the users to override the algorithm and heat the water in the tank immediately up to a certain set point. This provided the users with increased control and flexibility.

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*Figure 8: Typical installation of a Klugit device*

Graphical user interface, application

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*Figure 9: Screenshot of Klugit energy app*

# 4-Results

This section contains the results and discussion of the ongoing pilot project. In this section, both the quantitative results of the hot water forecasting, peak load reduction and avoided emissions are presented. In addition, the qualitative results of consumer interviews and surveys are presented. These surveys are included to help evaluate the impact of the Klugit devices on consumers’ lifestyles and comfort.

## Quantitative results

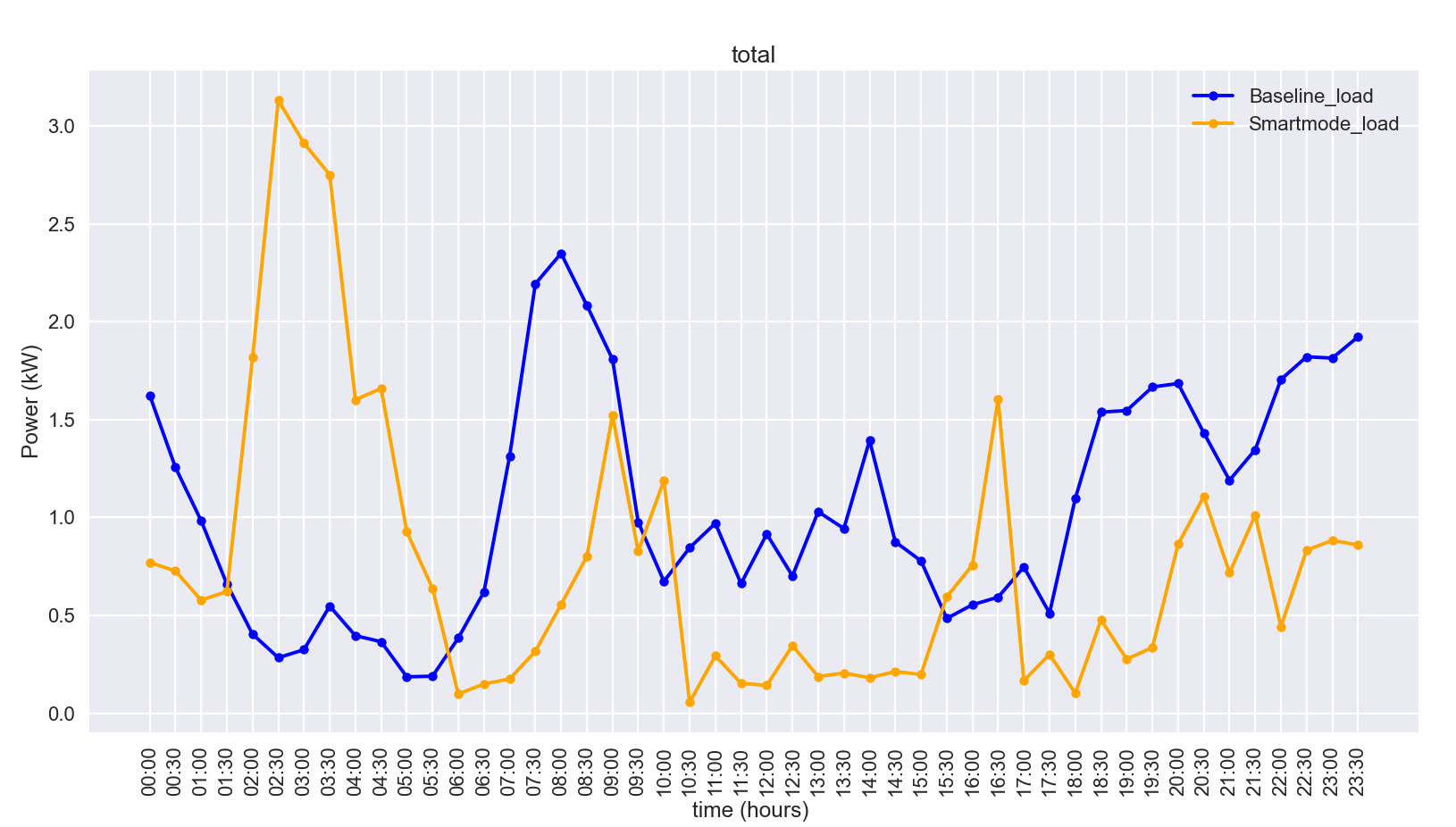
### Hot water forecasting and intelligent heating

The core function of the Klugit device is to predict 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
* Ancillary services

In this pilot project, only the first two benefits were assessed, namely peak shaving and load shifting. In addition to the abovementioned benefits, there is also the ability of the Klugit device to operate during high periods of renewable energy generation. By operating during these periods, the Klugit device can help increase the penetration of renewable energy technologies as well as utilising energy that may be curtailed if the Klugit device was not operating. To demonstrate the impact of the Klugit device on the operation of an EWH, Figure 10 compares the baseline operation for the average of July and August without any Klugit intervention to the same months where the Klugit was operating.

In Figure 10, the blue line shows the baseline operation of EWH without the operation of the Klugit device. The orange line shows the Klugit device operating in the smart mode to intelligently heat the water when it is needed. From the Figure, the heating load has been shifted out to the early morning and late afternoon periods and avoids the early evening peak. The result of this load intelligent heating is a reduction in the electricity used.



*Figure 10: Energy use in both smart mode and baseline modes*

The heating load was reduced by an average of 1.33 kWh/day per device for all Klugit devices which represented an average reduction in heating demand of 26.43%. The maximum reduction in heating use was 54.4% for a single Klugit while one Klugit saw the heating demand increase by 2.24%. This specific case is discussed in detail in the following paragraphs. The average daily energy use in the baseline and smart mode of the 10 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.

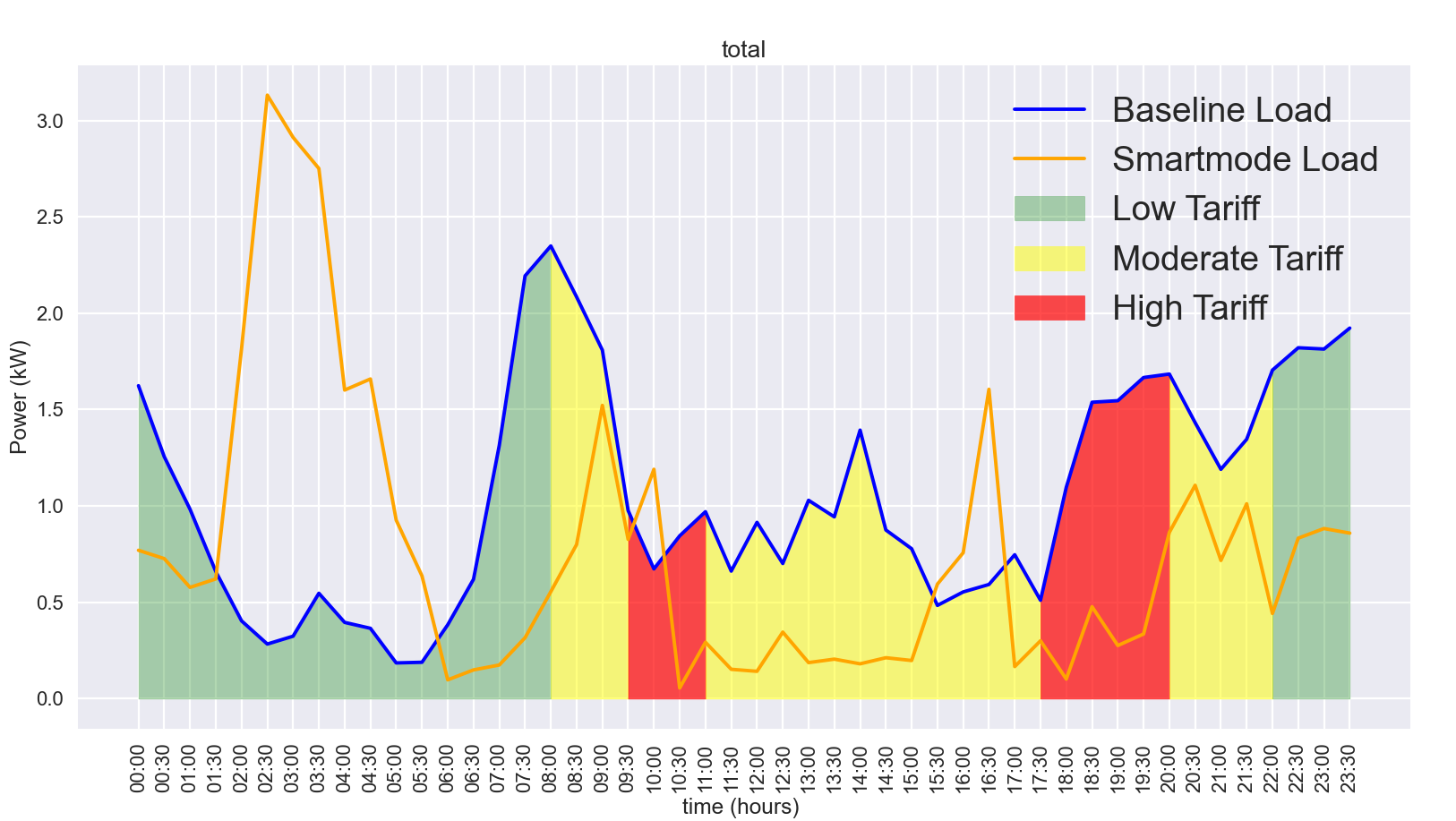
*Table 3: Daily energy use in both baseline and smart mode for 10 selected devices*

|  |  |  |  |
| --- | --- | --- | --- |
| Device | Baseline (kWh) | Smart mode (kWh) | Percentage 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 |

In addition to reducing the electricity used for water heating, the Klugit device also shifts the timing of the heating to periods with low energy tariffs which further reduces the energy bill of the consumer. 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, and 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 on the Figure below which shows the average baseline and smart mode operation for each hour in August. The green area represents periods of a low tariff, yellow indicated periods with moderate tariff and red denotes the periods with a high tariff. Again, the blue curve represents baseline mode operation, and the orange curve represents smart mode operation.

*Table 4: Tariffs used in São Miguel*

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



*Figure 11: Effects of load shifting due to Klugit device*

The figure above, Figure 11, 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. Combining the effects of reducing energy consumption and switching heating load from high tariff periods to low tariff periods, the smart mode operation reduces the energy cost to consumers. Based on the tariffs in place in this pilot project and Figure 11, consumers would pay 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. In this pilot project, the annual cost savings enjoyed by the consumer equate to €97.63 without affecting the thermal comfort of the consumer.

Chart, histogram

Description automatically generated

*Figure 12: Energy use of selected EWH with more energy consumption in smart mode*

During the pilot project, one EWH was operating in the smart mode which used more electricity compared to the baseline operation as is shown in Figure 12. 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.

Table 5 below shows a summary of the results for the 10 devices São Miguel pilot project. The table shows the average daily load reduction, the average load removed from the high tariff peak, the load shifted to the low tariff periods and finally the savings to the consumers' energy bill. In addition, the daily results are extrapolated to reflect annual results and are also shown.

*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 |

Therefore, a considerable amount of savings can be observed when this smart plug connected EWH is operating in smart mode. These savings in both energy and money are expected to increase with increasing numbers of installed Klugit devices. The above savings are direct savings accrued to the consumer.

### Peak load reduction

The ability of the Klugit device to reduce energy consumption and also shift load to periods of lower demand also has important benefits for the system operator. This is especially true in the case of São Miguel Island. As was mentioned previously, the island relies heavily on imported fossil fuel (both 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 those of 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 play a significant role, for example, between January and June 2021, the operational costs for the CTCL plant were on average €0.1241/kWh. The dispatch order is the order in which the different technologies are used to meet the demand of the system. 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 important in this analysis as a collection of Klugit 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 Klugit devices may operate as a Virtual Power Plant and have the ability to respond to certain requests from the system operator. In this pilot project, the Klugit devices were compared to the biogas and thermal plants, that is dispatch orders 3 and 4.

*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 |

Figure 13 shows the average energy mix for São Miguel for the 7th of July. 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 is a considerable part of the energy mix, especially from late afternoon onwards. The CTCL plant operates as a mid-merit plant to satisfy the remaining demand.

Chart

Description automatically generated

*Figure 13: Energy mix for 7 July 2021*

The quantity of electricity generated by each technology and its associated generation costs are reflected in Table 7 and the data are taken from (Electricidade dos Açores, 2021, 2020). The amounts of energy generated by solar PV and biogas are estimates, as they are independently owned and operated. The amount of energy generated by these two sources is not currently meaningful in the wider energy system of São Miguel.

*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 |

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”) and thus this is the initial target market for the Klugit devices 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 switch from liquefied petroleum gas (LPG) boilers (currently 88.3% of low voltage clients in the Açores islands) to electric water heaters.

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

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

The figure below shows the total generation profile for São Miguel (pink curve) and a load of these EWH 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 Klugit devise may be limited in this scenario, we can see an increase in the early morning load when the fleet of Klugit devices operates in smart mode. This impact is only expected to increase as the number of Klugit devices increases.

Chart, line chart

Description automatically generated

 Figure 14: Total load compared to baseline and smart mode demand of fleet of Klugit devices

This shift in early morning load from the Klugit devices operating in smart mode is shown in Figure 15. The pink line shows the existing generator load or standard load profile with passive EWHs, in other words, the current situation. The green lines represent the load curve if the aggregated EWH were operating in the smart mode in the different uptake scenarios. There is load shifting taking place, especially with an increase in the load in the early morning when the Klugit devices are heating. Installing the Klugit devices can reduce the total energy used by 2831.98 kWh per day or 0.21% of total energy under the medium uptake scenario.

Chart, line chart

Description automatically generated

*Figure 15: Baseline load vs smart mode load*

### Avoided emissions

The reduction in 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 gCo2/kWh in 2020 (Electricidade dos Açores, 2022) which is well above the average for Portugal which stands at 201 gCo2/kWh (Electricity Map, 2022). This highlights the importance of reducing emissions in the Açores islands, especially concerning 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 that can be displaced by the intelligent heating of the EWHs can be quantified. This is shown in Figure 16 which compares the thermal generation used for residential water heating in the passive (black) and smart modes (green) in the medium uptake scenario. This leads to a reduction of 0.37% of thermal generation or 2831.98 kWh per day with a generation cost of €0.1241/kWh. Solely based on the avoided generation from the CTCL plant, assuming a unit cost of a Klugit device of €85 per unit, the costs to equip 2127 residential homes with the device will be repaid in 1.4 years. This is in addition to the direct benefit to the consumer of over €100 annually based on reducing energy consumption.

Chart, line chart

Description automatically generated

*Figure 16: Energy from thermal generation from CTCL in baseline and smart mode*

Displacing this thermal generation will also have positive impacts on the emissions profile of EDA. Assuming that the aggregate group of intelligent EWH can displace 2831.98 kWh per day in the medium uptake scenario and using a carbon intensity of 670.729 gCO2/kWh for the thermal generation leads to a reduction of 693.31 tons CO2 per year in the emissions from thermal generation by simply utilising a Klugit device to manage the heating load of an EWH efficiently. In total, EDA emitted 368 000 tons of CO2 and therefore the aggregated Klugit devices can reduce this total by 0.18 % by only installing 2127 Klugit devices across São Miguel.

### Impact on physical infrastructure

Another possible benefit that intelligent EWH may offer the system operator is the reduction of load placed upon physical infrastructures, such as transformer units in low voltage networks. These EWH and other distributed energy resources may operate as so-called non-wires alternatives concerning investing in physical infrastructure upgrades. The information of 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 Figure 17. The total transformer load is shown in pink while the baseline, passive EWH demand is shown in blue. 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.

Chart, line chart

Description automatically generated

*Figure 17: Transformer load with baseline and smart mode loads*

Figure 18 shows the baseline transformer load in pink (Trafo Load). The green line is created by removing the baseline EWH load and replacing it with the intelligent load from the Klugit devices. There is load shifting occurring when the Klugit devices are operational. However, there is no peak reduction occurring. The peak load is slightly increased, and the minimum load is reduced. However, the objective of this group of aggregate Klugit devices is not related to minimising 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 physical infrastructure is considered. This is possible as the Klugit device transforms a passive EWH into a controllable distributed energy resource asset which can be used to satisfy several objectives from different agents.

Chart, line chart

Description automatically generated

*Figure 18: New (smart mode) and old (baseline) transformer load*

## Results from customer satisfaction survey

During the pilot project, consumer surveys and questionnaires were carried out to qualitatively measure consumer satisfaction with the Klugit device.

The quantitative survey consists of 20 questions, 18 categorical about recommendations, application features, design, installation and usability on a scale from 1 to 10: 1 multiple choice questions with 5 different prices, and a section for consumer suggestions for improvement. A copy of the survey has been attached as an appendix. At the end of the pilot project, the consumers gave the Klugit 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 plug to a family or friend.
* App features (with 8 questions): measuring the actual satisfaction with the features themselves, and seven others measuring the importance of the following list of characteristics:

1. Priority to the “low peak” period and avoid the “high peak” period to heat water
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 the satisfaction on the following topics:

1. Look 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 the satisfaction, safety and trust, and feeling:

1. Satisfaction with the ease of use
2. Degree of safety and trust when using Klugit
3. The feeling of having a Klugit

From a qualitative perspective, an interview script was prepared with 14 groups of small open questions that had 10 participants, each one asked the same group of questions individually, via remote interviews. The subjects were about the installation process, the existence of other water heaters, the previous use of devices to control the energy consumption, the difference between Klugit and those devices, lack of hot water during the test period, satisfaction, the use of the app and 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.

In the user satisfaction and recommendation, category four users gave the device a full 10/10 score while only two gave a score of under 5/10 and a median score of 8/10. Regarding the ease of installation, only two users gave a score 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. In terms of aesthetics and packaging of the product, the average score was 7.3/10 (median 8/10) and 7.6/10 (10/10) respectively. The average results of the survey are included in Figure 19 which reflects the average score of the survey participants.

*Figure 19: Average results from the consumer survey*

The functionalities or aspects of the device that the consumer valued as most important and would like to be included in future versions of the Klugit device are as follows (ranked most important to 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 visualise savings from the smart mode in the mobile application
6. Viewing the forecasted schedule for hot water demand
7. Reduce the thermal losses from the EWH
8. Reduce CO2 emissions from the energy used to heat the EWH

Notably, the consumers stated that the installation of the device was quick, easy, and simple to carry out. Several consumers were already using a programmable plug for their EWH which might make the installation process simpler for them. Concerning the two users who were not completely satisfied with the Klugit device, the major reasons were not related to the device. In one case, there was a weak Wi-Fi signal, and this made communication difficult between the device and the servers. 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 use 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 DWH needs of the consumer
* Once enough data has been gathered, modify the Klugit 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 being applied. 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 users who already have a standard programmable plug as was the case in several of the users in the Açores 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 the consumers.
* Add an option to switch the app to Portuguese (and other languages in the future) to improve ease of use.

# 5-Conclusion

This report has discussed the development, implementation and validation of a simple device to convert a passive Electric Hot Water heater into an intelligent, controllable distributed energy resource. This report also contains the details of a six-month pilot project carried out in conjunction with EDA on the island of São Miguel. The pilot project showed that these devices function well and are effective in terms of controlling the heating of water to provide benefits to both the consumers and the system operator.

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. This energy reduction led to an estimated average saving of 35.5% per consumer. In this pilot project, the annual cost savings enjoyed by the consumer equate to €97.63 without affecting the thermal comfort of the consumer. This monetary benefit exceeds the unit price of the Klugit device (€85 per unit) and with a lifetime of 5 years, the device can bring significant financial benefit to the consumers while maintaining their comfort.

The device can also provide both 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 peak load of the system, increase load during low demand periods, and displace electricity generated by fossil fuels. Using this fleet of 2127 intelligent EWHs, it is estimated that the devices can reduce total energy used on São Miguel by 2832 kWh per day or 0.37% of total energy through efficient heating of water. The energy savings from these devices in terms of avoided 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 CO2/year which is 0.18% of the total emissions of the company.

The report also showed that the device was well received by the participants in the pilot study and that it was easy to install and operate. Further improvements have been identified and will be carried out, but the qualitative results showed that the device did not significantly affect the consumer’s comfort. The consumers enjoyed the sense of control of their EWH and their ability to visualise their estimated savings and forecasted hot water demand.

In summary, this report has shown a simple and cheap 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 which are all especially important in island power systems such as São Miguel. Future work will look to increase the number of connected consumers and increase the communication capabilities of the device which will lead to increased controllability by the system operator.

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# Appendix

## Klugit satisfaction survey

|  |
| --- |
| English version |

Question Title

#### 1. How likely is it that you would recommend Klugit to a friend or family member?

NOT AT ALL LIKELY \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_ EXTREMELY LIKELY

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |

#### 2. How satisfied are you with Klugit's installation process?

Very satisfied

Satisfied

Neither satisfied nor dissatisfied

Dissatisfied

Very dissatisfied

#### 3. How satisfied are you with Klugit's ease of use?

Very satisfied

Satisfied

Neither satisfied nor dissatisfied

Dissatisfied

Very dissatisfied

#### 4. How satisfied are you with Klugit's app features?

Very satisfied

Satisfied

Neither satisfied nor dissatisfied

Dissatisfied

Very dissatisfied

#### 5. How satisfied are you with Klugit's mobile app look and feel?

Very satisfied

Satisfied

Neither satisfied nor dissatisfied

Dissatisfied

Very dissatisfied

#### 6. How satisfied are you with the Klugit product look and feel?

Very satisfied

Satisfied

Neither satisfied nor dissatisfied

Dissatisfied

Very dissatisfied

#### 7. How satisfied are you with the Klugit package?

Very satisfied

Satisfied

Neither satisfied nor dissatisfied

Dissatisfied

Very dissatisfied

#### 8. How confident and secure do you feel using Klugit?

Extremely confident

Very confident

Somewhat confident

Not so confident

Not at all confident

#### 9. What do you think would be a fair price to buy a Klugit (VAT included)?

50 EUR

70 EUR

100 EUR

120 EUR

150 EUR

10. What features are most important to you?

1. Priority to the "empty" period and avoid the "peak" period to heat water
2. Reduction of thermal losses from the water heater
3. Viewing savings in the app
4. Visualization of CO2 emission reduction
5. Forecast visualization for upcoming hot water needs
6. Request additional hot water when needed (Heat Now) in the app
7. Turn off smart mode when needed
8. Sustainable product, made from plastic taken from the oceans and packaged only in cardboard
9. Avoid connecting the water heater in parallel with other appliances, allowing the contracted power to be reduced

#### 11. How does having Klugit make you feel?

Very proud

Proud

Nothing special

Indifferent

Totally indifferent

#### 12. Anything else you would like to share?

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Versão Portuguesa

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| --- |
| Inquérito de satisfação Klugit |

### Questões

#### 1. Quão provável é recomendar a Klugit a um familiar ou amigo?

POUCO PROVÁVEL \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_ MUITO PROVÁVEL

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |

#### 2. Qual o grau de satisfação com o processo de instalação da Klugit?

Muito satisfeito

Satisfeito

Nem satisfeito nem insatisfeito

Insatisfeito

Muito insatisfeito

#### 3. Qual a sua satisfação com a facilidade de utilização da Klugit?

Muito satisfeito

Satisfeito

Nem satisfeito nem insatisfeito

Insatisfeito

Muito insatisfeito

#### 4. Qual a sua satisfação com as funcionalidades da aplicação?

Muito satisfeito

Satisfeito

Nem satisfeito nem insatisfeito

Insatisfeito

Muito insatisfeito

#### 5. Qual a sua satisfação com o aspeto da aplicação móvel da Klugit?

Muito satisfeito

Satisfeito

Nem satisfeito nem insatisfeito

Insatisfeito

Muito insatisfeito

#### 6. Qual a sua satisfação com o aspeto do produto Klugit?

Muito satisfeito

Satisfeito

Nem satisfeito nem insatisfeito

Insatisfeito

Muito insatisfeito

#### 7. Qual a sua satisfação com a embalagem Klugit?

Muito satisfeito

Satisfeito

Nem satisfeito nem insatisfeito

Insatisfeito

Muito insatisfeito

#### 8. Qual o grau de segurança e confiança que sente ao usar a Klugit?

Extremamente confiante

Muito confiante

Relativamente confiante

Não tão confiante

Nada confiante

#### 9. Qual acha que seria o preço justo para comprar uma Klugit (já com IVA)?

50 EUR

70 EUR

100 EUR

120 EUR

150 EUR

10. Quais as funcionalidades mais importantes para si?

Prioridade ao período “vazio” e evitar período de “ponta” para aquecer água

Redução das perdas térmicas do termoacumulador

Visualização das poupanças na app

Visualização da redução de emissões de CO2

Visualização da previsão para as próximas necessidades de água quente

Solicitar água quente adicional quando necessário (Heat Now) na app

Desligar o modo inteligente quando necessário

Produto sustentável, feito a partir de plástico retirado dos oceanos e embalagem apenas em cartão

Evitar ligar o termoacumulador em paralelo com outros eletrodomésticos permitindo diminuir potência contratada

#### 11. Como se sente por ter uma Klugit?

Muito orgulhoso

Orgulhoso

Nada de especial

Indiferente

Totalmente indiferente

#### 12. Existe mais alguma coisa que gostaria de partilhar?

## Açores users qualitative survey

English version

1. Did you have any difficulties installing the device? How long did the installation take?
2. What do you use to heat water? Only electric water heaters?
3. What did you have before Klugit? Watch plug? Why? What schedule? Did you have problems with the lack of hot water? Did you need to unplug the clock at some point?
4. What are the main differences you felt with Klugit? Which advantages and disadvantages?
5. Have you ever felt discomfort because the water was not hot enough?
   1. If so, were you able to identify the cause?
   2. Did you take any action?
   3. Have you changed any habits since you have Klugit installed?
6. Was there a hot water failure at any time?
   1. If so, was it due to overuse or failure to heat?
   2. Did you take any action?
7. Are you satisfied with our device?
   1. If so, what stands out best?
   2. If not, why?
8. How often have you used or opened our app? What are the most valued features?
9. Have you already used the “Heat now” feature? How many times? How often do you use it?
10. Did you manage to notice any savings or decrease in your electricity bill?
11. What do you think of the amount saved that is indicated in the app?
12. What price would you be willing to pay for the device if we told you that you are saving 100 EUR/year?
13. Have you ever shown Klugit to a friend or family member? What makes you proudest?
14. Would you recommend Klugit to a family member or friend?

Versão Portuguesa

1. Teve alguma dificuldade na instalação do dispositivo? Quanto tempo demorou essa instalação?
2. O que usa para aquecer água? Apenas termoacumulador?
3. O que tinha antes de Klugit? Tomada relógio? Porquê? Qual o horário? Tinha problemas de falta de água quente? Tinha necessidade de desligar a tomada relógio em alguma altura?
4. Quais as principais diferenças que sentiu com a Klugit? Vantagens e desvantagens?
5. Em algum momento sentiu desconforto pela água não estar suficientemente quente?
   1. Se sim, conseguiu identificar a causa?
   2. Tomou alguma acção?
   3. Mudou algum hábito desde que tem a Klugit instalada?
6. Houve falha de água quente em algum momento?
   1. Se sim, foi por excesso de uso ou por falha no aquecimento?
   2. Tomou alguma acção?
7. Está satisfeito com o nosso dispositivo?
   1. Se sim, o que destaca de melhor?
   2. Se não, porquê?
8. Com que frequência utilizou ou abriu a nossa app? Quais as funcionalidades mais valorizadas?
9. Já utilizou a funcionalidade “Heat now”? Quantas vezes? Com que frequência usa?
10. Conseguiu perceber alguma poupança ou diminuição na fatura de eletricidade?
11. O que acha do valor poupado que está indicado na app?
12. Que preço estaria disposto a pagar pelo dispositivo se lhe dissemos que está a poupar 100 EUR/ano?
13. Já mostrou a Klugit a algum amigo ou familiar? O que o faz sentir mais orgulho?
14. Recomendaria a Klugit a um familiar ou amigo?