INTEGRATED SCALABLE FRAMEWORK FOR SMART ENERGY MANAGEMENT

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ABSTRACT

The planet's resources experience fundamental troubles and unjust utilization. A large portion of the destruction is set off by using the planet's resources to produce energy of all kinds. To help with reverting the situation, there are mainly two approaches: firstly, to consider generating energy from clean and renewable resources, and secondly, to reduce the consumed energy by applying energy management systems. Due to the high energy consumption within the household sector, this paper aims to propose a dedicated household framework that tracks, predicts and manipulates the energy consumption of almost all appliances in the household; a sample household appliance is used to illustrate the main approach. The system is capable to track energy consumption and other related data directly from smart household appliances using their native connectivity and application programming interface capabilities, or from conventional appliances after equipping them with appropriate sensors and various Internet of Things (IoT) hardware. Once enough energy data is gathered, machine learning technologies will be applied to enhance the dataset and establish a solid background to predict energy consumption and apply the most suitable strategy from the available three strategies which most fits the appliance category. A case study implemented on a sample household appliance shows a possibility of reducing energy consumption by up to 22% by making a decision to replace the appliance with a more efficient one.

Keywords: household energy, household sector, IoT, predictive analysis, machine learning.

1 INTRODUCTION

Energy management systems can be defined as a set of rules and procedures applied to manage the energy journey beginning from production, through transfer and ending to consumption, to achieve the highest efficiency levels [1]. This paper will focus on proposing a framework to manage energy in the household sector because household energy consumption is considered a big portion of the total consumed energy worldwide, which is over 20,000 trillion Btu [2]. However, applying an energy management system in the household sector is a very challenging mission [3] and comes with many restrictions which can be summarized as: firstly, the challenge of reducing energy consumption while keep meeting the same level of comfort, which enhances the motivation of household occupants to continuously apply and use the system. Secondly, most household appliances are conventional appliances that lack connectivity capabilities. Thirdly, this field still does not offer a set of standards. Fourthly, the costs of the related technologies are still high and lack high levels of accuracy. Fifthly, there are still not enough reliable and dynamic open-source platforms that offer basic and common components which could be used for further adjustments and developments to gain more speed, reliability and higher quality.

Several approaches can be found in the literature, which can be grouped into four main groups: firstly, high-level energy management systems, which provide an abstract level of how to save energy without going into details. An example is the "Energy Management System designed for real Low-Voltage Distribution Networks with a High Penetration of Renewable Energy Sources" [4]. Secondly, the low-level systems, suggest building components on embedded systems and offer various interfaces. The main advantage of this approach is taking that of the host systems, and offering a high degree of flexibility to develop

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new and adjust current components. A good example of them is the Open Gate for Energy Management Alliance (OGEMA) 2.0 [5], illustrated in Fig. 1, which offers several basic and deeply integrated components related to security, authentication and user management modules.

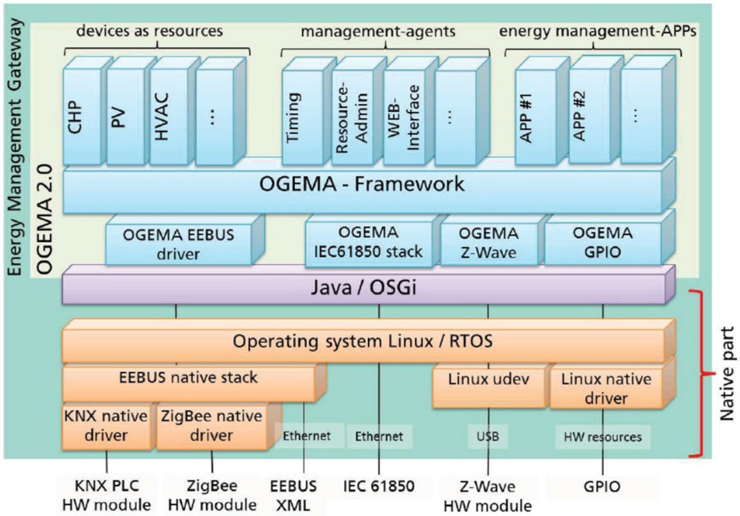

Figure 1: Energy management gateway architecture using OGEMA 2.0 [5].

Thirdly, the smart home energy management systems, which focus on utilizing an energy management system assuming having smart appliances, by providing advanced visualisations and illustration components, controlling possibilities including scheduling and routines to optimize the consumption, however, they did not provide a clear approach on how to deal with legacy and conventional devices. Self-Scheduling Model for Home Energy Management [6], and Smart Home Energy Management Framework dedicated to Internet of Things (IoT) Networks [7] are examples of these.

Fourthly, as illustrated by frameworks proposed by Bhayo et al. [8], [9] and Sutikno et al. [10], the integrated energy management systems supported by various hybrid clean energy generation schemes are equipped with storage capabilities to enhance sustainability and support the environmentally-friendly approach. However, the missing of using data-driven and prediction techniques to be able to deal with the near future events to act accordingly is considered a drawback which may reduce the efficiency of these types of frameworks. Also, relying on not fully-developed battery-based storage techniques may negatively affect the overall system reliability and dependability.

Finally, the data-driven predictive analysis-based systems, make use of machine learning (ML), artificial intelligence and IoT technologies. This approach can be seen in many frameworks that suggest using different predictive algorithms to provide energy consumption forecasting, such as the data-driven distributionally robust optimization based framework proposed by Saberi et al. [11], and the framework proposed by Pinto et al. [12] that makes use of the deep reinforcement learning approach..

Important to mention that these approaches suffer from the missing integrability of data retrieved from various hardware belonging to various vendors. Since this field suffers from missing standards, there is an essential need to offer a high level of integrability and data bridging to allow using different hardware, different standards and different data structures under one umbrella.

The next section describes the proposed framework which is an attempt to overcome most of the previously mentioned drawbacks and challenges.

2 THE PROPOSED FRAMEWORK

The proposed framework, illustrated in Fig. 2, is built upon the fact that household devices can be divided into three main categories: (1) Run-on-demand devices such as lights, (2) should-not-be-interrupted devices, that should not be manually switched on/off such as the refrigerator, (3) schedulable devices, these are devices that can be interfered with externally by switching them on/off; an example of these is the under-sink water heater or heating ventilation air conditioning systems.

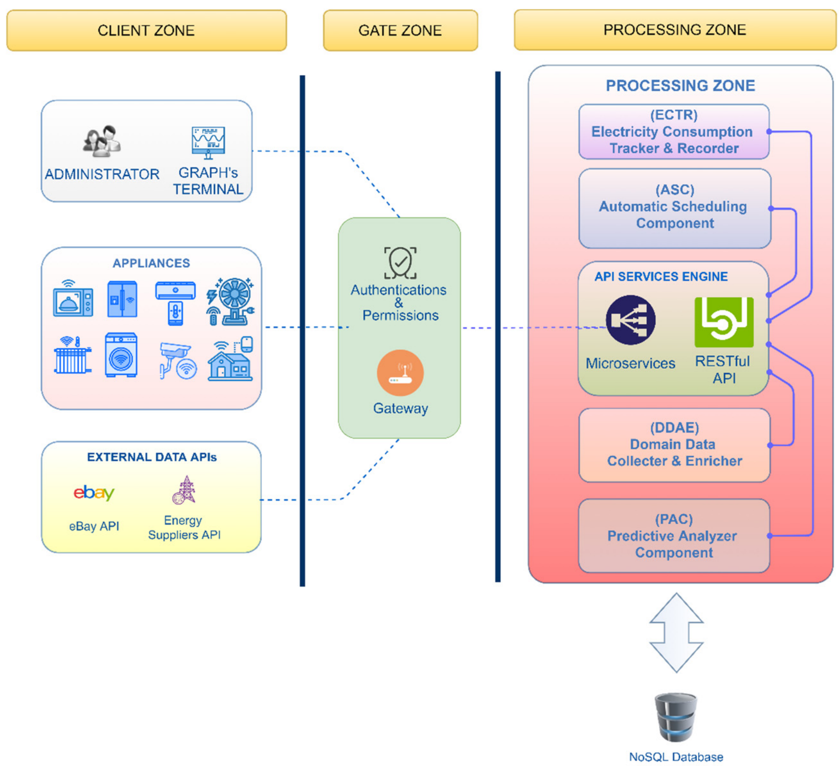

Figure 2: The proposed "Integrated Scalable Framework for Smart Energy Management".

It also suggests three different strategies to track, forecast and control the energy consumption of each group of devices accordingly. These strategies are: (1) Substituting devices based on energy consumption, which suggests tracking the energy consumption of the device, then suggests substituting it with a more energy-efficient one. Important to mention that old, inefficient appliances may only be used as spare parts, or to substitute other similar devices with higher energy consumption. (2) Substituting devices based on the usage percentage: this approach utilizes related artificial intelligence technologies to decide whether the device's size and volume are suitable for the targeted usage, for example, suggest substituting a 12 kg washing machine with a smaller one in a single-person household. (3) Automatic scheduling, which concentrates on tracking the energy consumption and the usage periods of a device, then predicting the future usage, and adjusting the running periods accordingly.

This paper focuses on the second strategy. Not each strategy applies to any household appliance, Table 1 shows which strategy can be applied to which device's group, whereas Table 2 shows a list of mainly used appliances, and their wattage, energy consumption (kWh) and average daily running periods in the household where the framework is applied.

Table 1: Device's groups and correspondent strategies.

Strategies	Device groups		
	Should not be switched off devices	Scheduled switch off/on devices	Run-on demand devices
Substituting devices based on energy consumption	X	X	X
Substituting devices based on the usage percentage	X	X	X
Automatic scheduling	–	X	–

Table 2: List of main appliances exist in the household where the case study takes place.

Appliances	Wattage	Energy consumption per hour	Average daily running periods
56 inch LED TV	125 W	0.13 kWh	3 hours
Refrigerator	300 W	0.3 kWh	24 hours
Coffee maker	800 W	0.8 kWh	0.5 hour
Vacuum cleaner	700 W	0.7 kWh	1 hour
Air fryer	1500 W	1.5 kWh	0.2 hour
Amazon Echo	3 W	0.003 kWh	3 hours
Bread toaster	800 W	0.8 kWh	0.3 hour
Clothes dryer	3000 W	3 kWh	0.4 hour
Laptop	250 W	0.3 kWh	4 hours
Electric iron	1200 W	1.1 kWh	0.3 hour
Under-sink water heater	1800 W	0.55 kWh	6 hours

As seen in Fig. 2, the framework consists of three main zones: (1) Client Zone: which consists of three main components including administrators, and a terminal to show the related graphs. Also, it includes the farm of related household appliances equipped with sensors. Finally, it has the external data application programming interfaces (APIs) to retrieve additional related external data. (2) Gate Zone: which is considered as a bridge between Client Zone and Processing Zone. It is responsible for passing the traffic and communication, applying the necessary authentication and permission procedures. (3) Processing Zone: Depending on the number of involved households, this zone may physically reside in the household, or the cloud. It consists of all components needed to process the data retrieved from the Client Zone which includes:

(a) Electricity consumption tracker and recorder which is responsible for tracking, cleansing, preparing and saving the energy consumption for each device.
(b) The automatic scheduling component is responsible for collecting all related data, then applying the ML techniques to predict the future behaviours of the household's occupants and devices, adjust their running periods, and offer the same comfort level, and reduce the energy consumption.
(c) API service engine (ASE) this component is the central point where all requests come in. It uses the state-of-art microservices topology to support the scalability to deal with an unlimited number of households.
(d) Domain data collector and enricher: the prediction process requires a huge number of data collected from the surrounding environment, such as internal and external temperatures, holiday periods, traffic, etc.; this component is responsible for choosing the suitable data nodes, the collecting and preparing them for example by applying some anomaly detection steps, and applying feature engineering aspects. Finally
(e) The predictive analyzer component where the ML process takes place by applying the cross-industry standard process for data mining beginning with business understanding, then data understanding, followed by data preparation, modelling, evaluation and deployment.

All components are connected to a NoSQL Database (MongoDB) which is chosen due to performance and scalability reasons. Data objects are collected from different sources with different structures so there is a need to be able to save these objects as they arrive without a need to a fix pre-structure.

The aim of applying ML and prediction techniques is to enhance the overall dataset giving a solid background to make proper decisions when applying the substitution strategy. Moreover, using the proposed framework on a wider scale with a huge number of households may deliver other advantages than directly reducing the energy consumption; these can be summarized as: (1) Providing the local energy providers with accurate consumption levels, so they can adjust their energy production accordingly. (2) Offering the appliances' manufacturers real-life running operational parameters of their devices, to let them spot the potential weak points and fix them in the upcoming versions. (3) Collected anonymous data may also assist the relevant governmental agencies to evaluate the reality and designing appropriate laws and regulations. Once enough dataset is collected from historical and predicted sources, the following equations will be applied to calculate the amount of saved energy:

$$\begin{aligned}&\text{Current Appliance Daily Average Consumption}_{(\mathrm{kWh})}(\text{CADAC})\\&=\ \text{MPC}_{(\mathrm{kWh})} *\ \text{ANHRRD}_{(\mathrm{hr})}\end{aligned}$$

where:
MPC = measured and predicted consumption in kWh; and ANHRRD = average number of hours refrigerator runs daily.

$$\begin{aligned}&\text{New Appliance Daily Average Consumption}_{(\mathrm{kWh})}(\text{NADAC})\\&=\ \text{NAC}_{(\mathrm{kWh})} *\ \text{ANHRRD}_{(\mathrm{hr})}\end{aligned}$$

where NAC = new appliance consumption in kWh.

3 CASE STUDY

As mentioned before, due to its integrability and scalability nature, the proposed framework establishes a wide basis that supports several strategies to reduce energy consumption in the household. However, in this case study, the focus will be on the first device's group "Should-not-be-switched-off Devices" such as refrigerator and the first strategy "Substituting Devices based on energy consumption".

The implementation phase aims to predict the energy consumption of the refrigerator, so it is possible to enhance the overall dataset which consists of the tracked energy consumption data and the predicted ones. This enables an accurate decision to replace or keep the refrigerator. It begins with collecting a number of data nodes from the surrounding area where the refrigerator is operating.

The data will be collected from three main sources: (1) Constants related to the device such as type, and size, which are entered by system administrators; (2) Sensing data retrieved from sensors; and (3) Specially constructed systems that use artificial intelligence techniques to read settings from conventional devices, such as the Refrigerator Temperature Settings Panel Reader shown in Figs 3 and 4. Finally, (4) External data retrieved from various APIs such as traffic and e-commercial platforms.

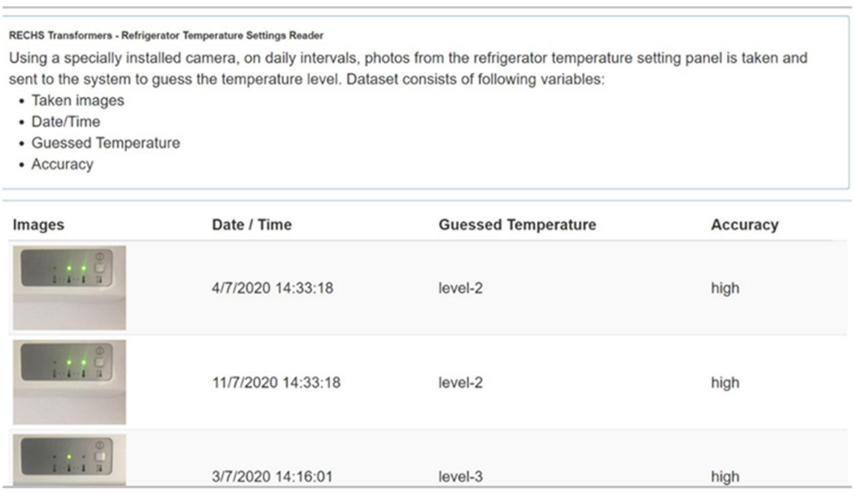

Figure 3: Transformers: Refrigerator temperature settings panel reader component.

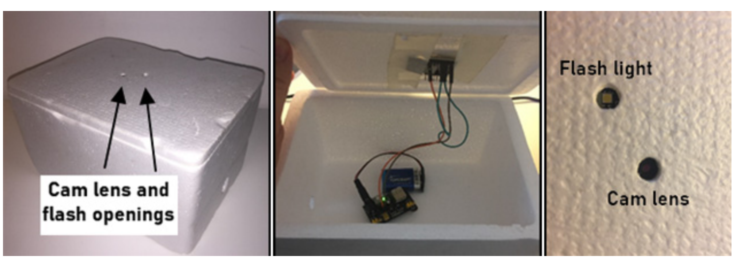

Figure 4: Refrigerator camera module used to feed the frig temperature settings panel transformer with proper images.

Then a list of verification, and cleaning actions are taken to ensure that only relevant data is considered. The outcome is shown in Table 3.

Table 3: Initial variables, sources, database field type, format, possible data range and some examples, with applied pre-processing.

Variable name	Source	Field type/ format	Example data/values	Action	Justification
Datetime	System	Datetime	2021-03-10 13:59:45	Removed	Not relevant for regression algorithms predictions
Internal temperature	Sensor	Float		Accepted	Shows high correlation with the target-feature
External temperature 5 cm	API	Float		Removed	Low target-correlation
External temperature 5 m	API	Float		Removed	See “External temperature 5 cm”
External temperature measured	Sensor	Float		Removed	See “External temperature 5 cm”
External relative humidity	API	Integer	0–100%	Removed	Low correlation score
External relative humidity measured	API	Integer	0–100%	Removed	Removed due to low correlation score
Internal relative humidity measured	Sensor	Integer	0–100%	Removed	A high percentage of missing data
Weather condition	API	Integer	Rainy, windy, stormy	Removed	Low variance score (0.24877371)
Refrigerator fullness	ML	Integer	0–100%	Accepted	It shows a high correlation score with the target-dependent feature
Occupants	ML	Integer		Accepted	The correlation score is not high, but also not low enough to discard this feature
Refrigerator temperature	ML	Integer	Level 1 – 6	Accepted	A high correlation score was calculated
Energy consumption	Sensor	Float	Watts/hour	Accepted	This is the target-dependent feature to be predicted measured in watts
Times door opened	Sensor	Integer		Accepted	Despite high feature-wise correlation with “Duration door left opened”, the field is kept to get better predictions
Duration door left opened	Sensor	Integer		Accepted	See “Times door opened”
Day type	System	Varchar	Weekend, weekday	Altered	Altered to (weekend: 0,1) because the effect of the day type affects the number of occupants staying at the household. The day type itself does not affect the prediction

Part of the data preparation is detecting the anomalies. This is done for the accepted datasets to make sure no anomalies are existing which may negatively be affecting the quality of the predicted models. Fig. 5 illustrates this process done for some selected data nodes.

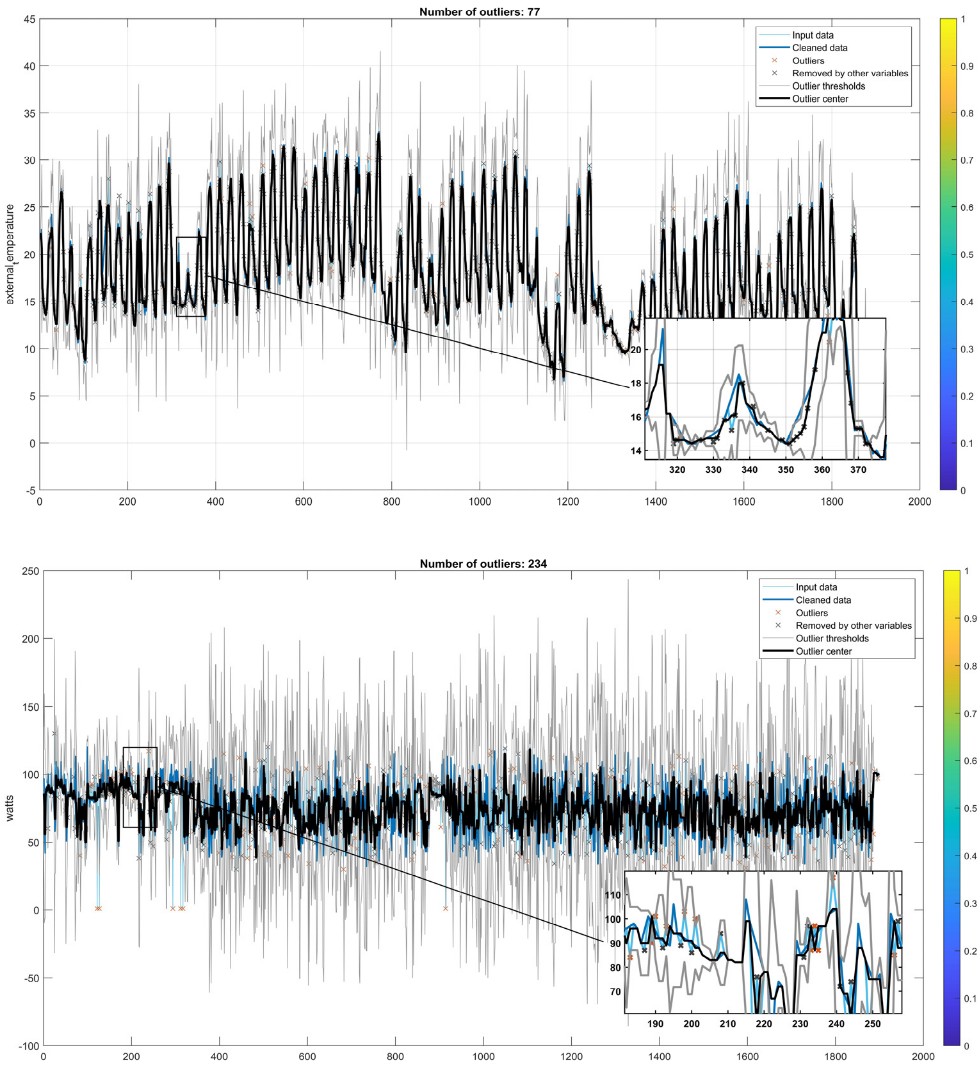

Figure 5: Anomaly detection plots of some selected features.

Once data is prepared, the modelling phase can begin to select the most suitable algorithm. Table 4 shows the resulted metrics which indicates that the models created using the Linear Regression (Multiple) are the most suitable for this purpose, where Fig. 6 shows the comparison among various algorithms and the targeted wattage derived from the verification dataset.

Table 4: Calculated regression algorithms' metrics.

Model	MSE	RMSE	MAE	R2
Polynomial regression	215.542	14.681	9.871	0.397
Linear regression (multiple)	430.948	20.759	15.519	–0.205
Random forest	8.363	2.892	1.708	0.977
Tree	8.332	2.886	1.685	0.977
Linear regression (simple)	22.513	4.745	3.359	0.937
kNN	13.519	3.677	2.254	0.962

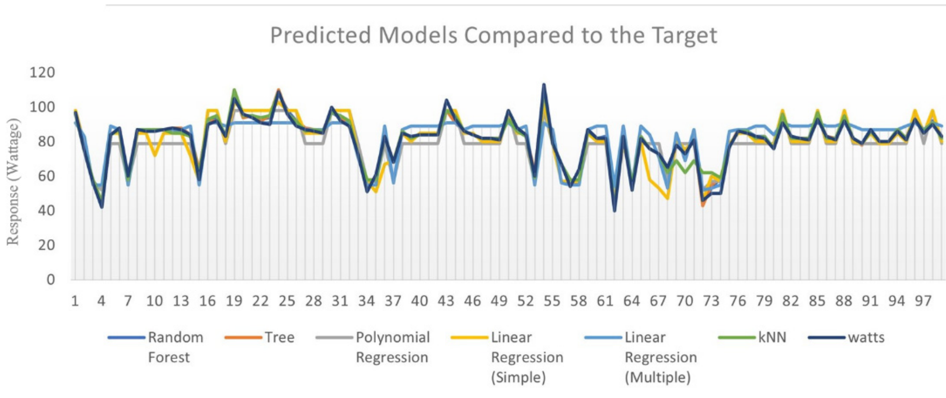

Figure 6: Regression prediction models compared to the verification wattage.

The collected historical data and the predicted data are used to save energy consumption by applying the previously mentioned substation strategy using the eBay product search API which returns a list of refrigerators with similar features to the sample refrigerator but have better energy efficiency. The saving of each result can be calculated using the previously mentioned equations, as follows:

$$\text{Energy Saving} = \frac{\left(\text{CADAC}_{(\text{kWh})} * 365_{(\text{day})}\right) - \left(\text{NADAC} * 365_{(\text{day})}\right)}{\text{CADAC}_{(\text{kWh})} * 365_{(\text{day})}} * 100\%$$

Applying this equation to different refrigerators shows that a refrigerator with the energy efficiency class A+++ may save energy up to 22%, as follows:

$$\text{CADAC}_{(\text{kWh})} = 0.081 * 8 = 0.648 \text{ kWh}$$

$$\text{NADAC}_{(\text{kWh})} = 0.063 * 8 = 0.504 \text{ kWh}$$

$$\text{Energy Saving} = \frac{(0.648 * 365) - (0.504 * 365)}{0.648 * 365} * 100\% = 22.2\%$$

This result can be even more enhanced when applying the framework to other appliances that can be switched on/off such as the under-sink immersion water heater. For this case, a manual or automatic switch mechanism, can be applied to cut off the energy consumption when the device is not used by setting a date, time and interval to start/stop the appliance.

4 CONCLUSION

This paper proposed a data-driven, predictive, scalable and integrated framework, which is applied to a household with a combination of smart and conventional appliances to gather various data nodes to predict the energy consumption for a sample appliance, using various regression algorithms which were evaluated via several evaluation metrics to decide for the most suitable model. Applying the mentioned strategy has shown an energy reduction of up to 22% for a sample device, the refrigerator, from the uninterruptible appliances category. The future work may include implementing the framework on a wider scale, covering more households, more appliances and applying other strategies.

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