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Machine Learning Prediction Based Integrated Smart Energy Management System to Improve Home Energy Efficiency

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***Abstract*—This paper proposes an integrated smart energy management system that applies different machine learning regression techniques to gather, enhance, and prepare various relevant data taken from the surrounding environment to predict and schedule the running periods of one of the schedulable appliances in the household. The system was applied to a case study with encouraging results showing energy consumption reduction rates up to 36%.**

Keywords: Energy management; machine learning; regression; household sector; IoT; predictive analysis

I. Introduction

As a set of roles and procedures, energy management systems are aimed at efficiently managing the energy journey, starting with the production of energy, transferring it forward and ending with its consumption [1]. According to the World Energy Consumption Statistics [2], the energy consumption within the household sector with approximate 20000 Trillion Btu is considered one of the biggest energy consumption sectors, therefore concentrating the efforts in this field may lead to increasing the overall energy efficiency. This paper proposes a dedicated smart energy management system based on machine learning techniques that sense and analyze the surrounding environment to predict, manage and reduce the energy consumption within the household for the immersion water heaters. It is a commonly known fact that the application of energy management systems within the household sector is a challenging task [3] that comes with several boundaries such as: firstly, the framework can be beneficial, only if household occupants are motivated to cooperate, therefore, it is essential that the system reduces energy consumption while keep maintaining the same levels of comfort. Secondly, most currently operating household appliances are conventional without any smart connectivity capabilities, therefore any smart system must analyze these appliances and offer a range of plug-in sensing hardware to enhance them. Thirdly, the lack of standards in this field adds additional challenges and complexity to delivering fast, accurate and reliable solutions using various hardware and software from different vendors without a need to build extra conversion modules. Fourthly, hardware and solution packages' prices are still high and unaffordable in this in-development and evolving field. Fifthly, open-source solutions have played an essential and pivotal role to speed up and enhance the quality of development in all fields where implemented. This can be seen in operating systems, browsers, and Internet areas. However, in the energy management systems area those kinds of reliable open-source platforms offering a set of basic components utilized for further development, and to enhance the system's overall reliability, stability and quality, still missing.

Reviewing the literature reveals many approaches to design and implementing energy systems, these can be put into four different groups: firstly, abstract-level energy management systems, which deliver answers on how to save energy on a high level, without going into details on how to practically do that. "Energy Management System designed for real Low-Voltage (LV) Distribution Networks with a High Penetration of Renewable Energy Sources" [4] is an example of such approaches. Secondly, bottom-level frameworks are based on embedded systems and offer a set of interfaces, taking advantage of the host systems' capabilities, and offering possibilities to develop new components and adjust existing ones accordingly. The Open Gate for Energy Management Alliance (OGEMA) 2.0 [5] is a good example of such a framework. It offers a number of essential and in-depth integrated components in many fields including security, authentication and user management. Thirdly, several integrated clean energy management systems are based on a hybrid structure of sub-systems that includes storage units. This approach can be seen in both frameworks represented by Bhayo BA, et al. [6] and Sutikno T, et al. [7]. However, both reviewed frameworks are missing the implementation of the data-driven prediction techniques which enable dealing with extraordinary future events. At last, the state-of-art, relatively newly introduced, data-driven, which are based on the prediction analysis that implements various machine learning techniques, IoT and AI technologies. A clear example of such approaches which rely on the implementation of predictive techniques to forecast future events can be clearly seen in two frameworks; the data-driven distributionally robust optimization (DRO) framework proposed by Saberi et al. [8], and the Deep reinforcement learning system presented by Pinto et al. [9]. One of the main drawbacks of frameworks in this area is the integrability problems due to the utilization of various hardware units from different vendors which is a result of not having standardized protocols and verbs. This shortage of standards opens the avenue to invent new systems which deal with this drawback by offering a set of integrational and data-bridging modules to make it possible for different hardware pieces and different data architectures to perform under one roof.

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II. THE PROPOSED FRAMEWORK

A general analysis of the various household appliances resulted in grouping those into three main categories: (1) Uninterruptable devices, which should not be manually shut on/off as refrigerators. (2) Demand-Run devices such as TV, lights, and (3) schedulable devices which includes all devices that can be scheduled to be shut down or run within certain periods according to needs and to optimize the energy consumption such as HVAC and immersion water heater. The proposed framework introduces three policies for tracking down, controlling and predicting the energy consumption of each category. These policies are (1) replacement of appliances based on their energy consumption by similar but more efficient ones. (2) Replacement of appliances based on their usage which is done by making use of a number of machine learning and artificial intelligence techniques to produce realistic predictions to decide whether the appliance size and capacity do not exceed the customer's needs. (3) Automated scheduling, which monitors, and tracks the behaviour and running periods of each device, then deliver future predictions based on the surrounding parameters such as the number of occupants, and special occasions (weekends for instance), which leads to adjusting the device's operations accordingly. The third policy will be the main focus of this paper. All previously mentioned policies are summarized in Table [1]. An example list of commonly used appliances, together with their energy consumption and daily running periods is illustrated in Table [2].

TABLE I DEVICES' CATEGORIES AND CORRESPONDING POLICIES

Policy	Device Categories		
	non-disturbable	*Programable*	*On-demand*
Cons.-based Replacement	✓	✓	✓
Usage-based Replacement	✓	✓	✓
Automated Scheduling	-	✓	-

The proposed system is mainly divided into three sections: (1) The Client Zone, which is divided into three modules: (a) administrators and graphical interface. (b) a number of household's conventional and smart devices farm, equipped with sensing units. and finally (c) external data APIs. (2) The Gate Zone, which represents the bridging path among both layers of client and processing zones. Its main duty is to observe and monitor the traffic and apply pre-implemented and defined authentication, security and permissions routines. (3) Processing Zone: Its meant to be logically separated from other zones to allow the physical implementation either to allow the physical implementation either within the household, in case, one household is involved, or in the cloud, once a huge number of households are participating in the system. It is mainly divided into five components required to deal with upcoming requests, these are: (a) Electricity Consumption Tracker & Recorder (ECTR) which has the main function to observe, cleaning and prepare the retrieved data. (b) The Automatic Heater Scheduler (AHS) which is specially dealing with data retrieved from the immersion water heater, by processing and cleaning it, then apply the proper machine learning technologies to forecast the future behaviours of the household occupants to adjust the device's operation periods accordingly, while keeping offering the same comfort level. The upcoming case study evolves around this approach. (c) The first touch point of all upcoming requests is called "API

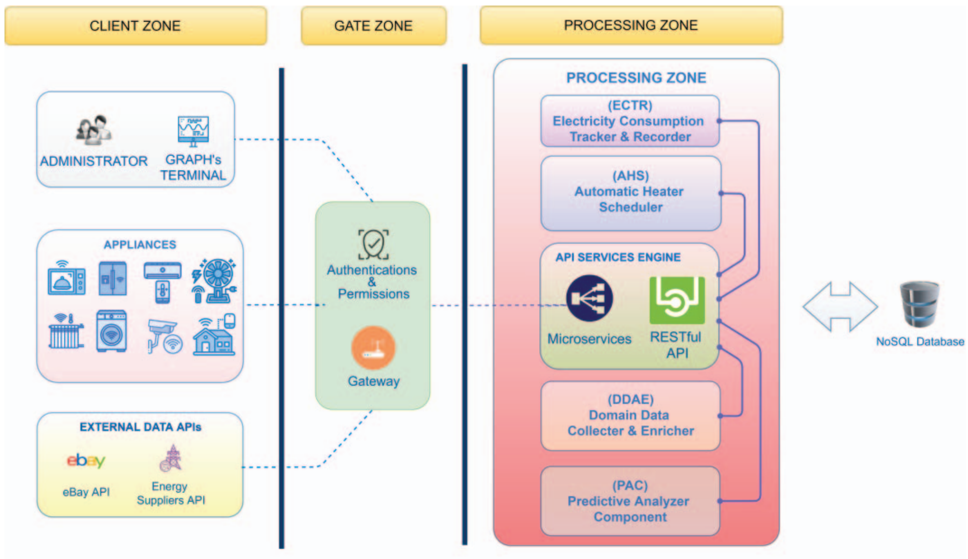

Figure 1: Proposed Integrated Smart Energy Management System to Improve The Energy Efficiency of Under Sink Storage Water Heaters (ISEM)

TABLE II COMMON HOUSEHOLD APPLIANCES AND THEIR WATTAGE

Devices/Appliances	Watt	Hourly energy consumption	Avg. daily operating hours
TV (56 Inch)	125W	0.13 kWh	3
Refrigerator	300W	0.3 kWh	24
Coffee machine	800W	0.8 kWh	0.5
Vacuum	700W	0.7 kWh	1
Fryer (Air)	1500W	1.5 kWh	0.2
Echo Device (Amazon)	3W	0.003 kWh	3
Toaster	800W	0.8 kWh	0.3
Tumble Dryer	3000W	3 kWh	0.4

Service Engine (ASE)". It is a set of services implemented using the state-of-art microservices topology supporting both vertical and horizontal scalability. (d) The Domain Data Collector and Enricher (DDAE) module is mainly responsible for collecting, processing, applying relevant anomaly detection acts and deciding on the most relevant data nodes from the huge number of data points collected from the local environment that directly or indirectly affect the energy consumption of appliances, for instance, the internal and external temperature, holidays, occupants number, traffic in the area, etc. (e) The core component "Predictive Analyzer Component (PAC)" where all ML activities occur based on the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework, which applies pre-defined steps including business understanding, data understanding, then data preparation, modelling, evaluating and deploying the results. To support the framework's overall performance and scalability to deal with all kinds of data objects retrieved from various nodes, the NoSQL MongoDB database is implemented, where data is stored without knowing its structure.

The application of ML and prediction techniques results in enhancing the dataset to offer enough, solid background to properly interact with the immersion water heaters running periods to consume the energy efficiently. Moreover, several other advantages may be resulted from implementing the framework on a wide scale, such as (1) supplying the local energy providers with accurate energy consumption forecasts allowing them to adjust their energy generation accordingly. (2) Supplying the manufacturers of devices with real-life operating parameters, allowing them to fix the weak points and add improvements to their devices. (3) Offering anonymous datasets to the related governmental departments to assist them to issue regulations and laws based on real-life scenarios.

III. Case Study

As previously mentioned, the scalability and integration attributes of the proposed framework allow the implementation of any of the mentioned strategies to manage and save energy consumption, however in this paper the focus will be on implementing the third strategy related to predicting and scheduling the running periods of the immersion water heater storage appliance. The energy consumed when water is not used is considered wasted energy and should be cut off. For this purpose, the experiment will be built around predicting the periods when the appliance is used, in other words when the water flow rates are not zero, and cut off the energy completely to prevent the re-heating cycles and thus save energy. Several parameters will be measured and collected to assist in predicting the running periods of the heater (when the heater will be used). Having this valuable information allows switching the device ON shortly before using it, and OFF when it is not used, for instance at night.

The data including the daily average energy consumption and the water consumption which were collected during the measurement phase of energy consumption and water rate data are illustrated in both Figures 2 and 3 accordingly. A quick comparison of both graphs shows that both energy and water consumption rises to start from the evening hours till around 9 pm, which matches the usual life activities in a household. However, the interesting part is the high energy consumption and zero water consumption in the period between midnight and the early morning hours. There we notice waste in the energy consumption which is used to keep the water's temperature without making any use of it.

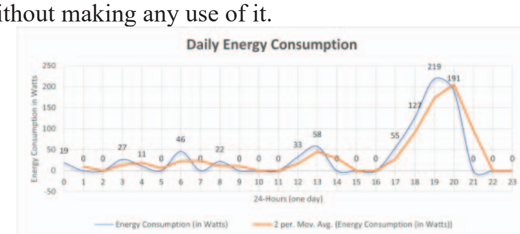

Figure 2: Measured Average Energy Consumption in 24 hours (in kWh), showing the moving average line (in orange)

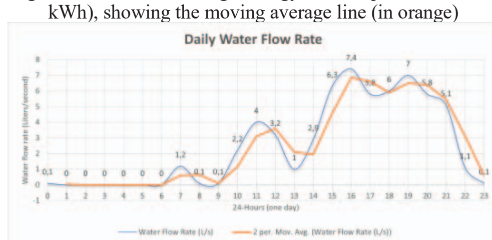

Figure 3: Measured Water Flow Rate in 24 hours (in Litre/second) with the orange line showing the moving average

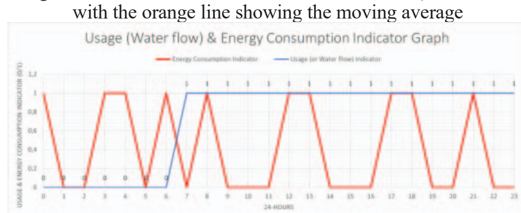

Figure 4: A comparison between the energy consumption (in kWh) and the Water Flow Rate or usage (in a litre(s)/sec.)

Comparing both figures is shown in the usage and energy consumption indicator graph in Figure 4, where the red line represents energy consumption, and the blue line represents the water flow. Important to mention that these lines do not show the quantity, but rather show one when there is a value, and zero when there is no value. it emphasizes the obvious idea that both peaks in the energy consumption and water usage are matched in the periods between 6:00 and 23:00 clock, taking into consideration that the heater volume of 10 litres plays a role in buffering hot water so there is no need for continuous heating up the water. In other words -roughly- the energy consumption increases when the water flow increases. However, according to Figure 4, although the water usage is zero the time between midnight and 6:00 clock in the morning, there are noticeable energy consumption values (or peaks). This occurs because the device attempts to keep the water at the same required temperature level when the water temperature drops.

A. Immersion Heater Data Preparation

To reduce the processing power and time, and to achieve high accuracy rates, data was prepared to decide on the most relevant and suitable independent variables, moreover, the records were run through several cleaning procedures to eliminate data noise, inconsistency, and irrelevant data records. These iterations include: (1)

Detecting Outliers and smoothing data as illustrated in Figure 5, and (2) Correlation assessment which is applied to the temperatures, humidity and heater-related parameters as shown in Figure 7. Applying the machine learning techniques using MATLAB results in creating the model illustrated in Figure 8.

B. Experiment's Conclusion

The system has achieved a noticeable energy-saving rate, approximately 36% which is equivalent to 10.872 kWh from the average daily total energy consumption of 1.244 kWh, by switching off the appliance when it is not used and switching it on shortly before using it again. This can be seen in Figure 6 which shows the same indicators after applying the Scheduling-Strategy policy, where the system has turned off the appliance during the night (between 00:00 and 5:00 clock), which leads to saving wasted energy.

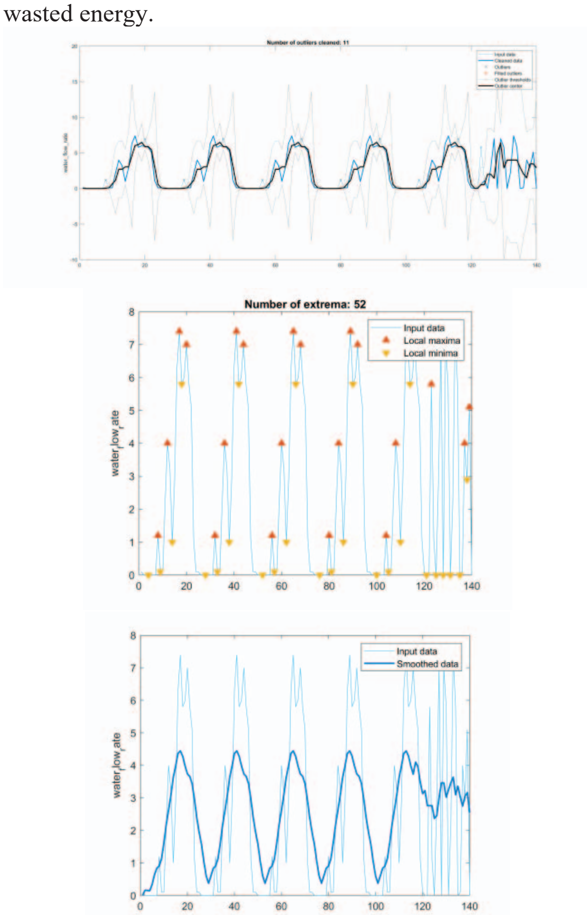

Figure 5: Three figures show the anomalies detection

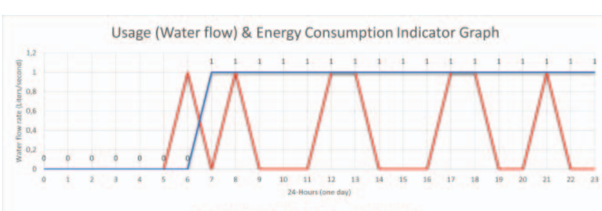

Figure 6: A comparison between the energy consumption (in kWh) and the Water Flow (usage) after applying the system

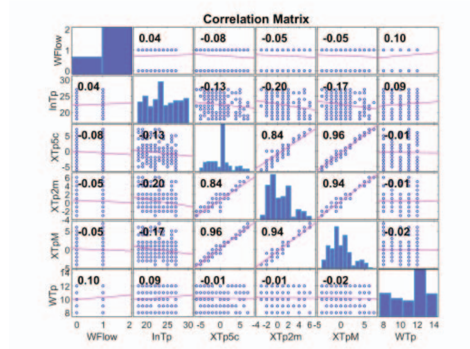

Figure 7: Correlation assessment of the target and temp. vars

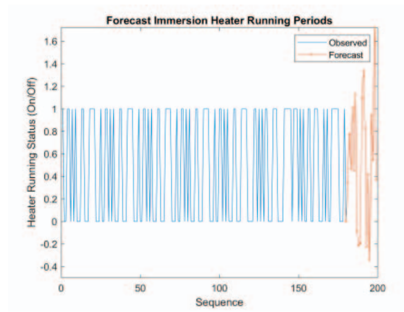

Figure 8: Observed and forecasted running periods

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