Joint Energy Demand Prediction and Control

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Abstract. Joint electricity predictor and controller (JEPAC) is a system that allows energy suppliers to better predict their electricity grid activity and then, optimize their energy production, management and distribution. In fact, the more accurate the prediction is, the lesser its negative impact on the economy and environment. Once the JEPAC system is installed in the energy consumer place, it will collect indoor ambient parameters and energy usage and thus predict the individual future consumption. This prediction will be frequently transmitted to the energy supplier as a formatted commitment then later, the same device will try to respect this commitment by adjusting wisely the user's appliances and HVAC. As a result, the energy supplier will then crowdsource the global energy demand by aggregating highly detailed individual consumption commitments. This will allow a better prediction and control of the future energy demand.

Keywords: Machine learning · Smart grid · Energy prediction and control · HVAC · Micro grid

1 Introduction

Forecasting accurate electricity consumption is a challenge. To perform this task, electricity suppliers use aggregate prediction due to the lack of information about individual electricity usage and behavior. If the utility suppliers predict energy consumption at the scale of the individual service subscriber, they can better manage their electricity grid; consequently, optimizing their energy production (for example; utilizing more renewable energy for example) and improve their distribution [2]. In this article, we propose a system that jointly predicts individual energy consumption and at the same time, wisely adjusts the HVAC in order to maximize the fit with the performed prediction. Then, the predicted individual usage details will be transmitted to the energy supplier as a commitment in a structured format that can be automatically processed. The energy consumption commitment will include a highly detailed prediction performed based on the frequency defined by the energy supplier. This process will be performed without impairing the privacy of the user. The individual energy usage will be locally performed and the commitment will only include timely aggregated energy consumption prediction. The energy supplier will therefore crowdsource all predicted data to build an accurate and detailed energy demand prediction. Ultimately the system will contribute to the emergence of a new electricity consumption

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paradigm. In fact, by helping energy supplier to better predict the energy demand, the latter will directly benefit of an important positive economic and environmental impacts that could be shared with the consumer as part of a reward system.

In Sect. 1, we introduce the JEPAC hardware architecture and the ambient parameters it collects. The Sect. 2 describes the machine learning technics executed by the device in order to predict the future energy consumption for an individual residence. In Sect. 3, we describe how the performed predictions are collected by the energy supplier and how JEPAC maximizes the respect of those predictions. In Sect. 4, we share the results of JEPAC device execution experience. Finally, in Sect. 5, we describe our future work perspectives.

2 Ambient Parameters Collection

In order to collect and determine indoor ambient parameters, the JEPAC device will use several sensors like temperature, humidity, Lux, etc., (*a*) [6]. The collected information is directly consumed for the needs of the device (to adjust HVAC or to perform an accurate prediction) or used to infer other information like user behaviour (example: sleeping mode, travel mode, etc.), [4]. The JEPAC device will certainly insure its primary role; adjusting appliances in order to reach a specific configuration of ambient parameters (like temperature, humidity, etc.) like shown in (*d*). As part of the system, the ambient parameters configuration could be specified by the end user or automatically determined [9]. Indeed, the JEPAC device will be connected to the internet via a regular internet router (c_1). It requires an internet connection to get access to some web services that provide external useful data that can't be collected by its own sensors like

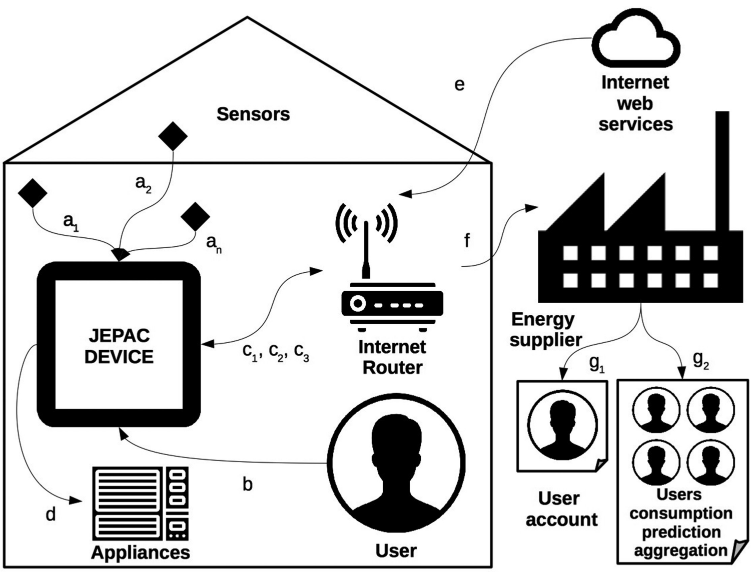

Fig. 1. The JEPAC system design

outdoor weather. The internet access represented by f will also allow the JEPAC device to send energy consumption commitments to a specific software hosted by the energy provider (c_2) to update the JEPAC embedded software when it is necessary (c_2).

3 Regression Based Prediction

By collecting indoor, outdoor and behaviour usage data [8], the JEPAC device will learn appliances configuration related to each ambient parameter combination (indoor measurements, outdoor measurements and other useful data like energy consumer behaviour). Then, the JEPAC device will use the predicted appliance configuration to deduct the user future energy consumption that will be communicated as a commitment.

In order to perform the energy consumption prediction, JEPAC uses an embedded machine learning algorithm [7] and produce a commitment. It includes the energy consumption prediction details during the entire following day. The prediction granularity is by default fixed to one prediction each hour. It means that each commitment will include 24 predictions that cover the energy consumption of the proceeding day. The number of predictions per day could differ depending on the accuracy level requested by the energy supplier. As represented in Table 1, the training set will be organized in separate slots, each represents a unique daily hour. Those slots will be used as a training base for a set of regressions that output a set of predictions related to each slot. Given that our regression model includes multiple regressor variables, we opted for multiple linear regression [1], i.e., for all $s = 1, 2, \ldots$:

$$\widehat{Y}_S = \widehat{\theta}_S \cdot X_S$$

$$\widehat{\theta}_S = \arg \min_{\omega \varepsilon \mathbb{R}^{\mathrm{d}}} \sum_{j=1}^{s-1} (Y_j - X_j \cdot \omega)^2$$

The entire slots predictions will represent the daily prediction that will be commuted as a commitment between the user and the energy supplier. It means that during a day, the machine learning will predict a set of $\hat{Y}$ where $\hat{Y}s = \{\hat{Y}0, \ldots, \hat{Y}s\}$ and s is the time slot identification. The training set consists of a consistent dataset composed of n records where each one is formed by a vector X which is paired with a value Y. Considering Xs as inputs vector in the slot S having I features and N samples. We can note it as follow: $X_s = \{x_s, 0,0 \ldots x_s, \mathrm{i}, \mathrm{n}\}$ where x_s, i, n is the *ith* input feature of the

Table 1. Training set for energy consumption prediction

Slot 0		Slot S			
X_0	Y_0	Xs			Ys
$X0, 0, 0 \cdots X0, \mathrm{i}, 0$	$Y0, 0$	$Xs, 0, 0$	$\cdots$	$Xs, \mathrm{i}, 0$	$Ys, 0$
$\vdots$	$\vdots$	$\vdots$		$\vdots$	$\vdots$
$X0, 0, n \cdots X0, \mathrm{i}, n$	$Y0, n$	$Xs, 0, n$	$\cdots$	Xs, i, n	Ys, n

nth JEPAC collected sample in a time slot *s*. *Y* is collected by the energy supplier using the smart meter installed at the user location.

3.1 Prediction Driven Control

The JEPAC device will act as a controller by adjusting the user appliances in order to respect the predicted electricity usage committed with the energy supplier. The appliance control can also be managed based on the user preferences and behaviour (sleeping mode, travel mode, outside mode, etc.). In fact, JEPAC gives the priority to the manual configurations in order to allow the user to have the final control of his appliances. JEPAC extends the reactive systems like the proportional controllers. Those ones are mainly based on a feedback loop that control their behavior dynamically. A simple reactive system acts as a proportional controller [10]. Like the non-smart thermostats, the proportional controller collects a current state $y(t)$ through its sensors and compares it with a desired one $z(t)$. Then, it calculates the difference between these values in order to determine the error $e(t)$ that will proportionally adjust the system to reach the desired output.

In general, the proportional controller algorithm follows a mathematical model that Eq. 1 describes. We consider that $u_{out}(t)$ refers to the proportional controller algorithm output. In our case, JEPAC is coupled with an HVAC system. So $u_{out}(t)$ refers to the control action taken by JEPAC and decides how much electricity the appliance system should supply to reach the setpoint. *Kc* refers to the proportional gain that adapts the magnitude of input signal collected by the JEPAC system to the magnitude used for by the JEPAC controller. However, in our system the reference setpoint is automatically defined and results from the combination between the commitment $c(t)$ and the user manual configuration $z(t)$. $y(t)$ refers to the current ambient state collected by the JEPAC system through its sensors. Finally, u_0 refers to the control action taken by JEPAC which is necessary to maintain ambient parameters at the steady state when there is no error.

$$u_{out}(t) = K_c(z(t) - y(t)) + u_0 \tag{1}$$

The JEPAC augments the proportional controller by taking the committed energy consumption into consideration. As in Fig. 2, rather than trying to reach only a user defined setpoint $z(t)$, the current system reference will consider a combination of the energy consumption commitment $c(t)$ (resulting from the learning model) and the user desired setting $z(t)$. The JEPAC system is composed by coupling the prediction system (represented by the orange boundary) and the controller (represented by the blue boundary). The prediction system forecasts the future energy consumption, and sends it to the energy supplier as a commitment $c(t)$. This commitment will be used the following day in conjunction with the manual settings $z(t)$ in order to control the HVAC. More specifically, the system will update the reference initially defined by the user with a temporary setpoint respecting the commitment made between the energy consumer and the energy supplier. The difference between the commitment setpoints and the user defined ones should be smaller than a certain ratio in order to ensure that the system meets at a certain level the user comfort desires. Also, the end user has the possibility to explicitly ignore the commitment setpoint.

In general, by adding the commitment data to the initial control system reference, different strategies with different advantages and costs can be considered. As represented in the Eq. 2, the function $f\,(c(t),\, z_s(t))$ that represents the new control system entry can be updated by the user as needed. More strategies will be part of our future work.

$$u_{out}(t) = K_c(f(c(t),\, z(t)) - y(t)) + u_0 \tag{2}$$

Algorithm 1. Future consumption prediction and commitment

Result: Energy supplier aggregates individual predictions to evaluate the global energy demand

1. Use an existing training set to train the machine learning algorithm;

for *each day d (example: Sep 1st)* **do**

  for *each time slot s (example: 13h00)* **do**

    1 Provide an energy consumption prediction $\hat{Y}_S$;

    2 Add $\hat{Y}_S$ to the commitment $c(t)$ (that includes the next day electricity consumption);

  end

  3.1 As soon as the commitment $c(t)$ is fully completed, display its content in a user-friendly way (Optional step);

  3.2 Wait for the users' commitment confirmation $c(t)$ (Optional step); 4 Send the commitment $c(t)$ to the energy supplier;

  5 At d, energy supplier will $c(t)$ energy consumption commitment; 6 At $d+1$, Adjust the users' appliances in order the respect the energy consumption communicated in $c(t)$;

  7 At $d+1$, the energy supplier compares real energy consumption et to the predicted one $e^!(t)$ previously communicated in $c(t)$ to produce δ. δ measure how much the energy consumption prediction (already received) fits with the real consumption;

  8 In addition to $e(t)$, the energy supplier will use δ rate to determinate the right charging formula;

end

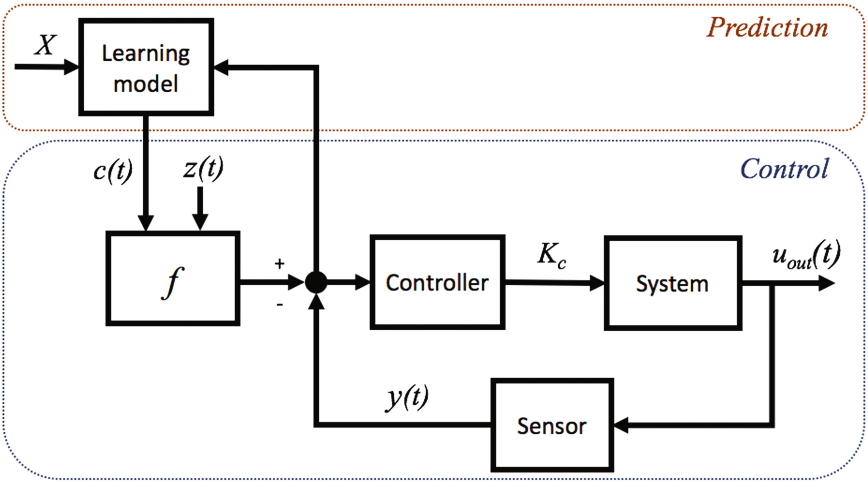

Fig. 2. Joint energy demand prediction and control

3.2 The Energy Demand Prediction

As in g_1 (Fig. 1), the energy supplier will receives energy consumption commitments from users. It aggregates those commitments $c(t)$ in order to build a larger prediction concerning specific clusters of energy consumers like an energy consumer in some specific area. This aggregation will be performed by a software hosted by the energy supplier. In fact, thanks to the formatted structure of data provided through the users commitments, the electricity demand can be predicted through a simple aggregation of the commitments records. Furthermore, energy supplier can perform a horizontal aggregation; Aggregating all the energy consumption prediction records provided by different commitments in a specific for a specific time [5]. As a result, the energy supplier can predict easier the future activity of its electricity grid. For example; it can determine how many turbines it has to activate, estimates better the electricity demand in a specific geographic zone and improves renewable energy use thanks to more predictable energy demand [5]. As represented in g_2, by using δ rate, the energy supplier will reward the user based on the fitting level between the real and the predicted energy consumption. The more the commitment $c(t)$ (predicted energy consumption) is respected, the more the reward will be. To encourage energy consumers adhesion, the commitment respecting rate will be used exclusively to reward the user. In case of non respect, the user will pay the energy supplier with the regular pricing formula. He will only lose the reward.

4 Simulation

For experimentation, we use a public dataset provided by OpenEI that includes 8760 data records collected hourly at the same residential place.[1] Each data record includes energy consumption details such as heating, electrical devices, etc. This dataset was used to train a machine learning algorithm in order to perform the energy consumption prediction. The data is ordered by time stamps and splitted into 24 slots where each one represents a unique daily hour (Example: 13h00). The JEPAC machine learning algorithm runs a set of multiple linear regressions applied on each time slot. In terms of technology, we use Statsmodels Python module to implement multiple linear regression using an ordinary least squares method to perform the multiple linear regressions [3].

4.1 Tests and Results

Once trained, JEPAC system was able to predict the next day energy consumption details with an accuracy equal to 91,83% for all of the 24 time slots. In Fig. 3, we used an error bar representation to visualize the predicted energy consumption during one day. It also includes the prediction errors in comparison with real energy consumption for the same day. We noticed that the prediction accuracy was lower in a small number of time slots due to the lack of data used for the simulation (in our case, it concerns the time slots 18:00, 19:00 and 20:00. This gap will be naturally filled once the training set grows up. Once a consistent training set will be constituted, the JEPAC machine learning algorithm will be able to extend its prediction over one day. Finally, once the prediction will be performed, it can be sent to the energy supplier as well as to support the JEPAC controller to better adjust the user devices' respecting the energy consumption commitment [5].

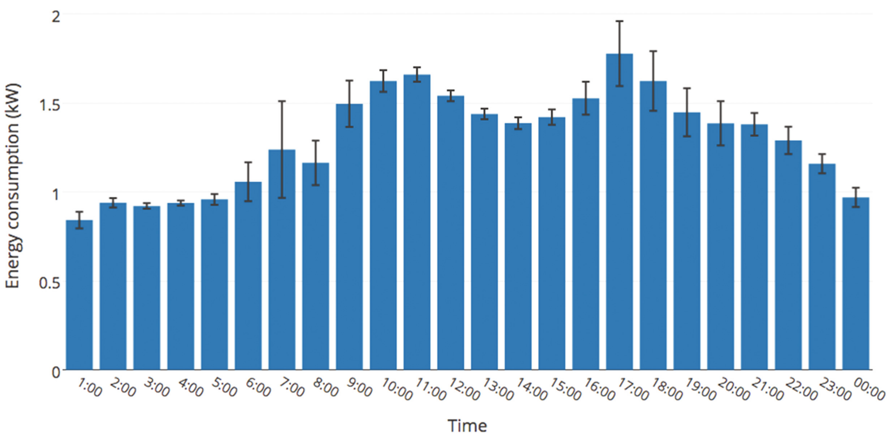

Fig. 3. Energy consumption prediction for an entire day (kW)

[1] Link: OpenEI.org - EPLUS TMY2 RESIDENTIAL BASE.

5 Future Work

Our future work will focus on two main research paths: Firstly improving and expending our prediction driven control system and secondly building an incentive plan for reward distribution by taking into regards the engagement user.

5.1 Expension of the Current JEPAC System

Our future work will extend the combination strategy between the manual and the commitment based setting. Represented by the function $f\,(c(t),\, z(t))$, we intend to build a more complex combination function that combines user's convenience and commitment respect.

5.2 Reward Distribution Incentive Plan

In order to encourage users to respect the commitment, the energy supplier should have an efficient incentive plan. In our future work, we intend to build an incentive and fair rewards distribution model that could improve users' envolvement in such energy consumption program.

References

1. Peck, E., Montgomery, D., Vining, G.: Introduction to Linear Regression Analysis, 4th edn. Wiley (2015)
2. Rogers, A., Jennings, N.R., Ramchurn, D., Vytelingum, P.: Putting the smarts into the smart grid: a grand challenge for artificial intelligence. Commun. ACM **55**(4), 86–97 (2012)
3. Hayashi, F.: Econometrics. Princeton University Press (2000)
4. Srinivasan, S.V., Gao, G., Holben, B., Stankovic, J., Field, E., Whitehouse, K., Lu, J., Sookoor, T.: The smart thermostat: using occupancy sensors to save energy in homes. In: Proceedings of the 8th ACM Conference on Embedded Networked Sensor Systems, SenSys 10, pp. 211–224. ACM (2010)
5. Yu, J.Y.: Distributed Forecasting and Pricing System (2014)
6. Peffer, T., Aragon, C., Perry, D., Pritoni, M., Meier, A.: How people use thermostats in homes: a review. Build. Environ. **46**(12), 2529–2541 (2011)
7. Parker, L.E., Edwards, R.E., New, J.: Predicting future hourly residential electrical consumption: a machine learning case study. Energy Build., 591–603 (2012)
8. Newman, M.W., Yang, R.: Learning from a learning thermostat: lessons for intelligent systems for the home. In: Proceedings of the 2013 ACM International Joint Conference on Pervasive and Ubiquitous Computing, UbiComp 13, pp. 93–102. ACM (2013)
9. Iskin, I., Daim, T.U.: Smart thermostats: are we ready? Int. J. Energy Sect. Manage. **4**(2), 146–151 (2010)
10. Doyle, J.C., Francis, B.A., Tannenbaum, A.R.: Feedback Control Theory. Dover Publications, New York (2009)