2016 IEEE International Conference on Smart Grid Communications (SmartGridComm): Data Management and Grid Analytics and Dynamic Pricing

Distributed Machine Learning based Smart-grid Energy Management with Occupant Cognition

Hang Xu, Hantao Huang, Rai Suleman Khalid and Hao Yu
School of Electrical and Electronic Engineering,
Nanyang Technological University, Singapore 639798
Email:haoyu@ntu.edu.sg

Abstract— **It is challenging to process real-time data analysis and prediction for a smart grid in a building with consideration of both occupant profile and energy profile. This paper proposed a distributed and networked machine learning platform on smart gateways based smart grid. It can analyze occupants motion, provide short-term energy forecasting and allocate renewable energy resource. Firstly, occupant profile is captured by real-time indoor positioning system with Wi-Fi data analysis; and the energy profile is extracted by real-time meter system with electricity load data analysis. Then, the 24-hour occupant profile and energy profile are fused with prediction using an online distributed machine learning with real-time data update. Based on the forecasted occupant motion profile and energy consumption profile, solar energy source is allocated on the additional electricity power-grid in order to reduce peak demand on the main electricity power-grid. The whole management flow can be operated on the distributed smart gateway network with limited computation resource but with a supported general machine-learning engine. Experiment results on real-life datasets have shown that the accuracy of the proposed energy prediction can be 14.83% improvement comparing to SVM method. Moreover, the peak load from main electricity power-grid is reduced by 15.20% with 51.94% energy cost saving.**

I. Introduction

Modern building/complex can be provided power from main electricity power-grid and additional power-grid of renewable solar energy. Since the main electricity power-grid may experience a huge peak of load, one can allocate solar energy to rooms to reduce the peak load. A cyber-physical energy management system (EMS) development is thereby increasingly needed with an intelligent load forecasting. Therefore, a smart-grid system with ambient intelligence (AmI) becomes the interest. The AmI here refers to machine-learning based data analysis within environment in response to the presence of people [1]. An indoor AmI can extract feature from power, positioning and environmental data, which is helpful to improve the comfort level for household occupants. As for the current indoor AmI, the first challenge is how to deal dynamic ambient change with real-time response because the processing backend in cloud takes latency. And the second challenge is how to address scalability and robustness in a distributed solution for a large space. Therefore, a real-time data analysis on a distributed machine learning platform with networked smart grid architecture is needed.

Acknowledgement: this work is sponsored by grants from Singapore MOE Tier-2 (MOE2015-T2-2-013), NRF-ENIC-SERTD-SMES-NTUJTCI3C-2016 (WP4) and NRF-ENIC-SERTD-SMES-NTUJTCI3C-2016 (WP5)

To tackle above mentioned challenges, the works in [2] [3] [4] have introduced day-ahead short-term forecasting methods, which are however not based on a real-time data analysis with limited energy reduction without consideration of features from occupant activity. This paper has proposed a distributed data analysis platform that can support short-term load forecasting, which can extract features from both real-time occupant positioning data as well as energy data. Based on this platform, a solar energy allocation problem is formulated to reduce the peak load in the main electricity power-grid. The whole smart energy management flow for buildings can be summarized as three steps: real-time data sensing, occupant profile and energy profile extraction, and solar energy source allocation, which is mapped on the computational resource limited smart-gateway network without using cloud.

The core contribution here is one common online sequential machine learning algorithm with incremental least-square solver, which can provide a fast data analysis of different training samples. It is 14.83% more accurate when compared to the Support Vector Machine (SVM) based data analysis. Moreover, based on the predicted occupant profile and energy profile, the solar energy can be allocated with a peak load reduced by 15.20% and energy cost saving by 51.94% when compared to the static prediction based approach.

The rest of this paper is organized as follows: The system architecture is introduced in Section II. In Section III, the proposed machine learning algorithm and profile extraction are elaborated. The solar energy allocation for peak load reduction is introduced in Section IV. Experiment results are presented in Section V with conclusion drawn in Section VI.

II. System Architecture

In this section, we have introduced the system architecture of smart home with multimodal sensors and smart gateways. Occupant cognition can be performed by machine learning algorithms using sensed data. Based on extracted occupant profile and energy profile, various services can be provided using data analysis platform.

978-1-5090-4075-9/16/$31.00

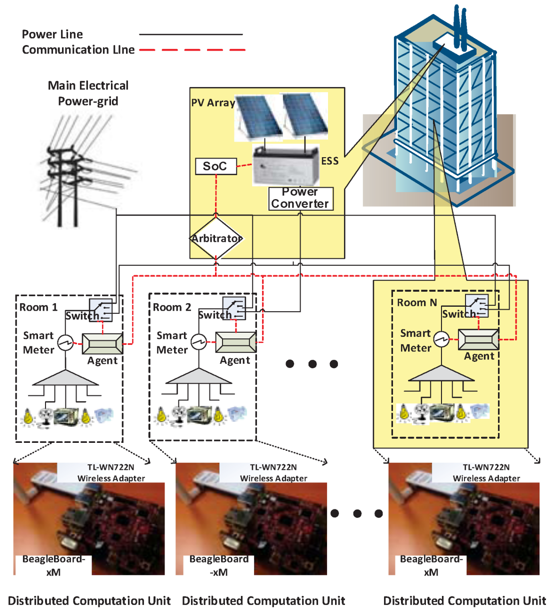

Fig. 1: Hybrid smart building architecture

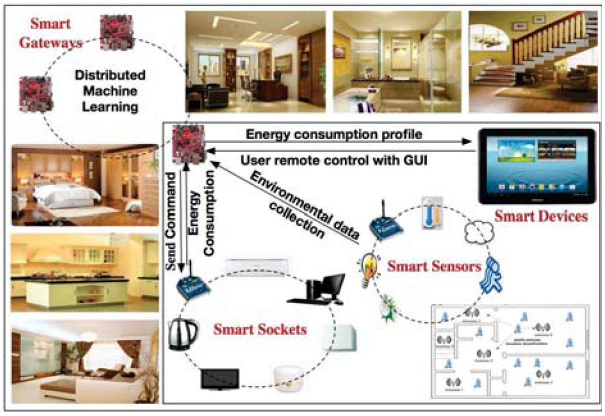

Fig. 2: The overview of smart home management system

A. Smart Grid Architecture

The overall real-time distributed system for energy management of a smart building is illustrated in Fig. 1. This EMS infrastructures are implemented inside rooms based on smart-gateway network for collecting and analyzing energy data [5]. The components can be summarized as following:

- *Main electricity power-grid* is the primary energy supplier for household occupants from external electricity supplier, whose price is much higher than solar energy.
- *Additional electricity power-grid* is the solar photovoltaic panel whic is constructed by connected photovaltaic cells [6], [7]. There is also energy storage system used for storing solar energy which can be used in the peak period.
- *Smart gateways* are used for storage and computation as the control center. In our system, an open source hardware BeagleBoard-xM with AM37x 1GHz ARM processor is selected for performing intense computation.

In this distributed system, decision-making is performed independently in each smart gateway. As such, even if one gateway at room level is broken down, the overall system functionality will not be affected. Moreover, by utilizing the solar energy, the EMS can schedule electrical appliances in a room based on the demand-response strategy.

B. Data Acquisition Sensor

Various sensors are deployed in a smart home system to collect environmental data, energy data and positioning data towards energy prediction and management as shown in Fig. 2. Main sensors are listed as following:

- *Smart power-meter* (or *smart plug*) can real-timely sense current and record energy consumption data. It can also perform two-way communication with monitor. Moreover, it includes a switch which is used to change the supplied energy source physically.
- *Wireless adapter* is used to capture the Wi-Fi package from mobile device according to IEEE 802.11 protocol. These packages are stored, parsed and computed in BeagleBoard-xM for positioning [8].

C. Data Analysis Platform

The major computation is performed on smart gateways in a distributed fashion. This distributed computation platform can perform real-time data analysis and store data locally for privacy purpose. Data communication between gateways is performed through Wi-Fi using message passing interface (MPI). Also, shared machine learning engine is developed in the smart gateway to perform real-time feature extraction and learning. Therefore, these learnt features such as occupant positioning and energy demand, can be the input of services such as additional energy allocation.

III. Machine Learning based Load Forecasting with Occupant Cognition

A. Machine Learning on Distributed Smart Gateway Platform

To extract occupant profile and energy profile, we deployed an online sequential extreme learning machine (ELM) [9] and realized it on distributed smart gateway platform. We developed an incremental least-square solver for low computation complexity.

Given N arbitrary distinct training samples $\mathbf{X} = \{\mathbf{X_B}, \mathbf{X_E}\} \in \mathbb{R}^{N\times m}$, $\mathbf{Y} = \{\mathbf{Y_B}, \mathbf{Y_E}\} \in \mathbb{R}^{N\times 1}$, where $\{\mathbf{X_B}, \mathbf{Y_B}\}$ are training samples for extracting occupant profile and $\{\mathbf{X_E}, \mathbf{Y_E}\}$ represent training samples for forecasting energy profile, which will be elaborated in III-B and III-C.

The output function of standard ELM model with activation function $h(x)$ and L hidden nodes can be modeled as:

$$\sum_{j=1}^{L} \boldsymbol{\beta}_j h(w_j x_i + b_j) = y_i, i = 1, 2, ..., n \tag{1}$$

Above formula can be rewritten into following matrix form [9]:

$$\mathbf{H}\boldsymbol{\beta} = \mathbf{Y} \tag{2}$$

Here, $\mathbf{H} \in \mathbb{R}^{N\times L}$ is the result of sigmoid activation function $h(x)$.

By minimizing $||\mathbf{H}\boldsymbol{\beta} - \mathbf{Y}||_2$, the output weight $\boldsymbol{\beta}$ is calculated in training process. The solution can be expressed as

$$\boldsymbol{\beta} = (\mathbf{H^T H})^{-1}\mathbf{H^T Y}, \mathbf{H} \in \mathbb{R}^{N\times L} \tag{3}$$

1) Incremental Least-Square Solver: This least square problem of minimizing $||\mathbf{H}\boldsymbol{\beta} - \mathbf{Y}||_2$ is the most time consuming part in training process. With the number of hidden node increasing, the training error reduces at the expense of increasing computational cost. So an incremental solution is needed for low computation complexity with the hidden node number adjustment.

We utilize Cholesky decomposition with computational cost $O(\frac{1}{3}L^3)$ to solve the least square problem. Compared with SVD and QR decomposition with computational cost $O(4NL^2 - \frac{4}{3})$ and $O(2NL^2 - \frac{2}{3}L^3)$ respectively, its symmetric and incremental property saves half memory and reduces the computational cost [10].

Here, $\mathbf{H}_L$ is denoted as the matrix with L number of hidden neuron nodes ($L < N$). We decompose the symmetric positive definite matrix $\mathbf{H}^T\mathbf{H}$ into

$$\mathbf{H}_L^T\mathbf{H}_L = \mathbf{G}_L\mathbf{G}_L^T \tag{4}$$

where T is transpose operation of the matrix and $\mathbf{G}_L$ represents a low triangular matrix.

$$\begin{aligned} \mathbf{H}_L^T\mathbf{H}_L &= \left[\mathbf{H}_{L-1}\ h_L\right]^T\left[\mathbf{H}_{L-1}\ h_L\right] \\ &= \begin{pmatrix} \mathbf{H}_{L-1}^T\mathbf{H}_{L-1} & \mathbf{p}_L \\ \mathbf{p}_L^T & s \end{pmatrix} \end{aligned} \tag{5}$$

where h_L is the new column added by increasing the number of hidden nodes L and can be calculated from (1).

The Cholesky matrix can be expressed as

$$\begin{aligned} &\mathbf{G}_L\mathbf{G}_L^T \\ &= \begin{pmatrix} \mathbf{G}_{L-1} & \mathbf{0} \\ \mathbf{q}_L^T & t \end{pmatrix} \begin{pmatrix} \mathbf{G}_{L-1}^T & \mathbf{q}_L \\ \mathbf{0} & t \end{pmatrix} \end{aligned} \tag{6}$$

As a result, we can easily calculate the $\mathbf{q}_L$ and scalar t for Cholesky factorization as

$$\mathbf{G}_{L-1}\mathbf{q}_L = \mathbf{p}_L,\ t = \sqrt{s - \mathbf{q}_L^T\mathbf{q}_L} \tag{7}$$

where $\mathbf{G}_{L-1}$ is the previous Cholesky decomposition result and $\mathbf{p}_L$ is known from (5). In this way, we can continue use previous factorization result and update only according part. When $l = 1$, $\mathbf{G_1}$ is a scaler and equals with $\sqrt{\mathbf{H_1}^T\mathbf{H_1}}$.

2) On-line Sequential Model Update: Our proposed online sequential ELM model is updated constantly with new training samples added to training set $\mathbf{X}$. The online sequential ELM includes two phases: initialization phase and sequential learning phase [11].

In the initialization phase, the output weight $\boldsymbol{\beta}^{(0)}$ can be estimated by:

$$\boldsymbol{\beta}^{(0)} = \mathbf{Q}_0\mathbf{H}_0^T\mathrm{Y}_0 \tag{8}$$

where $\mathbf{Q}_0 = (\mathbf{H}_0^T\mathbf{H}_0)^{-1}$ can be calculated using the incremental least-square solver.

In the sequential learning phase, the new training data arrives one-by-one. Given the $(k+1)_{\text{th}}$ new training data arrives, the output weight $\boldsymbol{\beta}^{k+1}$ can be calculated as [11]:

$$\begin{aligned} &\mathbf{Q}_{k+1} = \mathbf{Q}_k - \mathbf{Q}_k\mathbf{H}_{k+1}^T(\mathbf{I} + \mathbf{H}_{k+1}\mathbf{Q}_k\mathbf{H}_{k+1}^T)^{-1}\mathbf{H}_{k+1}\mathbf{Q}_k \\ &\boldsymbol{\beta}^{k+1} = \boldsymbol{\beta}^k + \mathbf{Q}_{k+1}\mathbf{H}_{k+1}^T(\mathbf{Y}_{k+1} - \mathbf{H}_{k+1}\boldsymbol{\beta}^k) \end{aligned} \tag{9}$$

B. Occupant Profile Extraction

Active occupant motion usually indicates the high level of active behavior of occupants in the room [12]. Rooms inside the same house have vastly different occupant profiles due to different functionalities. Therefore, we extracted occupant profiles for different rooms respectively [8]. For each room *i*, there are four states represented by S for occupants positioning:

$$S = \begin{cases} s_1: 0 & \text{no occupant in the room } i \\ s_2: 0 \longrightarrow 1 & \text{occupants entering the room } i \\ s_3: 1 & \text{occupants in the room } i \\ s_4: 1 \longrightarrow 0 & \text{occupants leaving the room } i \end{cases} \tag{10}$$

where motion state S is detected by indoor positioning system via Wi-Fi data every minute. The probability of occupants motion for room i can be expressed as:

$$b(t) = \frac{T(s_2) + T(s_3)}{T}, t = 1, 2, 3, ..., 96 \tag{11}$$

where, $T(s_j)$ represents the time duration with corresponding state s_j. $b(t)$ is occupants motion probability of room i in T time interval. Here, we set the T as 15 minutes resulting in 96 intervals in one day. Based on the motion probability $b(t)$, the probability of active occupants can be expressed as:

$$\mathbf{B} = [b(1), b(2), b(3), ..., b(96)] \tag{12}$$

Since the occupant profile $\mathbf{B}$ on the d_{th} day is extracted based on trend of previous days, we choose previous seven-day occupant profiles as training data $\mathbf{X_B}$ and the profile on 8_{th} as $\mathbf{Y_B}$, which can be shown as:

$$\begin{aligned} \mathbf{X_B} &= \{\gamma_d\sigma \cdot \mathbf{T}_d | 1 \leqslant d \leqslant 7\} \\ \mathbf{Y_B} &= \{\mathbf{B}_d | d = 8\} \end{aligned} \tag{13}$$

Where, $\mathbf{B}_d$ represents the occupant profile on the d_{th} day and $\mathbf{T}_d = \mathbf{B}_d^T$. Here, γ_d is the daily weight assigned to each training data and σ is the weaken factor used to reduce the effect of abnormal data.

Since the latest actual sample has most significant effect on prediction, the arriving new data should be paid more attention using heavy weight. The daily weight γ is set as:

$$\gamma_{d-1} > \gamma_{d-2} > ... > \gamma_{d-7} \tag{14}$$

Moreover, it is possible that some abnormal data samples appear suddenly. According to historical occupant profiles, extremely abnormal samples can be detected using the average motion probability, which is shown as:

$$\sigma = \begin{cases} 1 & \frac{1}{2}A \leqslant \bar{\mathbf{B}} \leqslant \frac{3}{2}A \\ 0.1 & \bar{\mathbf{B}} < \frac{1}{2}A \text{ or } \bar{\mathbf{B}} > \frac{3}{2}A \end{cases}$$
$$s.t \quad \bar{\mathbf{B}} = \frac{\sum\limits_{t=1}^{96} b(t)}{96} \qquad A = \frac{\sum\limits_{d=1}^{7} \bar{\mathbf{B_d}}}{7} \tag{15}$$

where $\frac{3}{2}A$ is defined as the upper bound and $\frac{1}{2}A$ is defined as the lower bound.

C. Energy Profile extraction

Energy profile $\mathbf{E}$ consists of the hourly energy consumption $e(t)$ in the time span of 24 hours whose characteristic in different weather conditions and different day types are various. The energy profile $\mathbf{E}$ can be expressed as:

$$\mathbf{E} = [e(1), e(2), ..., e(24)] \tag{16}$$

To forecast the energy profile on $(d+1)_{\text{th}}$ day, we choose training data $\mathbf{X_E}$ with features as shown in Table I and $\mathbf{Y_E}$ as the actual energy profile on the d_{th} day.

TABLE I: Input features for short-term load forecasting

Inputs	Descriptions
1	Date type: weekday is represented by 1 and weekend is represented by 0
2-25	T(d-7,t), T(d-6,t), T(d-5,t), T(d-4,t), T(d-3,t), T(d-2,t), T(d-1,t): Temperature of the seven days preceding to the forecasted day at the same hour
26-49	H(d-7,t), H(d-6,t), H(d-5,t), H(d-4,t), H(d-3,t), H(d-2,t), H(d-1,t): Humidity of the seven days preceding to the forecasted day at the same hour

IV. Energy Management for Peak Load Reduction

During the peak period, peak demand may exceed the maximum supply level that the main electricity power-grid can provide, resulting in power outages and load shedding. Moreover, the electricity price of the main power-grid is higher during the peak period. In this paper, we scheduled the solar energy as the additional power supply to compensate the peak demand in the main electricity power-grid. Using profiles of occupant motion and energy consumption, we apply solar energy allocation to rooms with a fast and accurate short-term load prediction.

A. Problem Formulation of Solar Energy Allocation for Peak Load Reduction

We denote the generated solar energy $G(t)$ and the energy demand $D(t)$ from main electricity power-grid at time t. The allocated solar energy $A(t)$ is determined by the energy management system, which is shown as:

$$A(t) = \boldsymbol{f}(\mathbf{B}, \mathbf{E}) \tag{17}$$

where the $\mathbf{B}$ and $\mathbf{E}$ are the predicted occupant profile and energy profile respectively.

Here, we formally defined objectives of allocating solar energy.

Objective 1: A set of solar energy allocation strategy $A(t)$ should be determined to minimize the standard deviation of energy consumption from main electricity power-grid with peak load reduction.

$$argmin(dev \sum_{t=1}^{t=24}(D(t) - A(t))) \tag{18}$$

Objective 2: The daily energy cost is expected to be minimized through solar energy allocation strategy. The daily energy cost minimization can be expressed as

$$argmin \sum_{t=1}^{t=24}(D(t) - A(t))p(t) \tag{19}$$

Where $p(t)$ represents the real-time electricity price.

Naturally, a constraint should be taken into consideration that the allocated solar energy $A(t)$ cannot exceed the available amount of solar energy at anytime.

$$A(t) \leqslant L(t) \tag{20}$$

where $L(t)$ represents the amount of solar energy stored in the energy storage system at time t.

B. Solution with Short-term Load Prediction by Fused Occupant Profile and Energy Profile

To formally illustrate the proposed energy management method, two factors should be described firstly.

$P_B(t)$ represents the probability of active occupant motion for the whole house at the time t:

$$P_B(t) = \sum_{i=1}^{M} \alpha_i \theta_i b_i(t), \quad 0 \leqslant \alpha_i \leqslant 1 \tag{21}$$

where the $b_i(t)$ is the occupant motion probability for room i and θ_i is the statistical information of occupants staying in room i. M is the number of rooms. Since household appliances in each room are diverse resulting in various energy consumption levels, weight parameter α_i is set according to the energy consumption characteristic of each kind of room.

$P_E(t)$ is the proportion of energy consumption at time t:

$$P_E(t) = \frac{e(t)}{\sum\limits_{t=1}^{24} e(t)} \tag{22}$$

where $e(t)$ is components of the predicted 24-hour energy profile.

Since the energy consumption is likely to increase when occupants motion probability is increasing [12], the peak load period can be detected by fusing $P_B(t)$ and $P_E(t)$. The probability of load peak $P_{\text{peak}}(t)$ can be denoted as:

$$P_{\text{peak}}(t) = \eta P_B(t) + (1-\eta)P_E(t), 0 \leqslant \eta \leqslant 1 \tag{23}$$

When $P_{\text{peak}}(t)$ exceed $\frac{2}{3}$, it is regarded as the load peak moment. At such moment, solar energy will be allocated to alleviate the load from main electricity power-grid.

The expected amount of solar energy allocation $A_E(t)$ can be determined by

$$A_E(t) = \Phi(\mathbf{E(t)} - \bar{\mathbf{E}}) + \Psi P_B(t) \tag{24}$$

where the parameter Φ and Ψ are set by occupants according to actual energy demand. $\bar{\mathbf{E}}$ is the average energy consumption during 24 hours.

The actual amount of solar energy allocation is

$$A(t) = \begin{cases} A_E(t) & A_E(t) \leqslant (G(t) + L(t-1)) \\ L(t-1) + G(t) & A_E(t) > (G(t) + L(t-1)) \end{cases} \tag{25}$$

Here, $L(t-1)$ is the total amount of remained solar energy until time $t-1$. $G(t)$ is the generated solar energy. $G(t) + L(t-1)$ represents the available amount of solar energy at the time t. If the generated solar energy $G(t)$ is more than the allocated solar energy $A(t)$, the remained solar energy $L(t)$ will be accumulated for next allocation period.

$$L(t) = L(t-1) + (G(t) - A(t)) \tag{26}$$

Fig. 3 shows the system flow based on proposed machine learning on distributed smart-gateway platform.

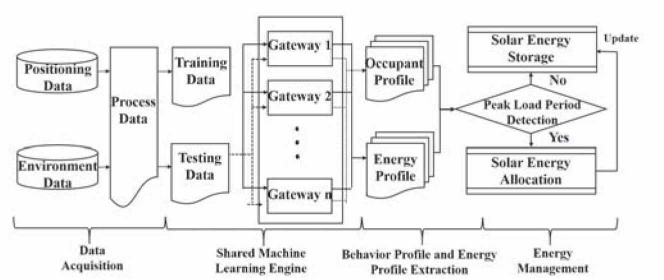

Fig. 3: Flow based on distributed machine learning on smart gateways

V. Experimental Results

A. Setup and Benchmark

In this section, we evaluated the forecasting performance of distributed online sequential ELM in comparison with SVM [13]. Then we verified the proposed energy allocation method in comparison with static prediction based approach. We utilized one dataset from the Smart* Home Dataset [14] and one dataset provided by Energy Research Institute of Nanyang Technological University. To illustrate the capability of the proposed method for the energy cost saving, we choose a real-time electricity pricing strategies from [15]. The occupant motion prediction and energy consumption forecasting are both running on the computing platform of BeagleBoard-xM with AM37x 1GHz ARM processor. Experiment set-up is summarized in Table II.

In this experiment, we first predicted 24-hour occupant profile using previous 7-day motion probability and then forecasted 24-hour energy consumption using environmental factors. Then we estimated the prediction accuracy using mean absolute percentage error (MAPE) and root mean square error (RMSE). MAPE and RMSE can be defined as:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}|\frac{P(t)-R(t)}{R(t)}| \tag{27}$$

TABLE II: Experiment set-up

Parameter	Value
No. of Gateway	5
Initial Training Days	7 Days
Continue Evaluation Days	23 Days
Environmental Data	30 Days
Motion Data	30 Days
Solar PV area	25-50 m^2
House area	1700 ft^2

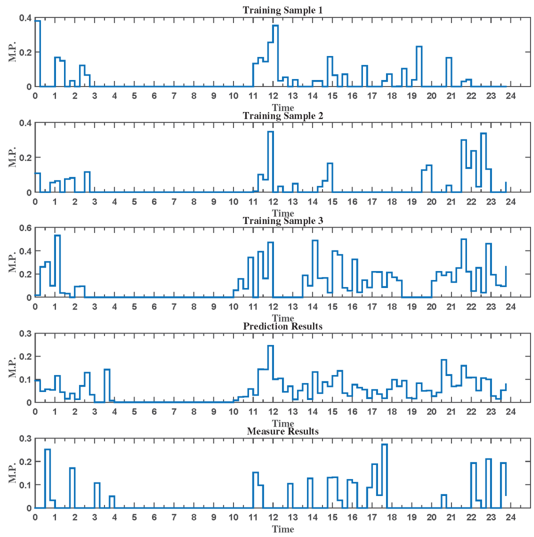

Fig. 4: Motion probability within 15 minutes interval in a living room (3 training samples, 1 predicted result and 1 actual result).

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(P(t)-R(t))^2} \tag{28}$$

where P(t) is the prediction value and R(t) is the actual value.

Finally, based on the predicted energy profile and occupant profile, we allocated solar energy for reducing load peak demand and saving energy cost.

B. Occupant Profile Extraction

We firstly predicted 24-hour occupant profile in six rooms: basement, bedroom, guest room, kitchen, living room and master room. Fig. 4 shows the predicted motion probability in 15 minutes interval of living room. And corresponding training data and measured data are also displayed to demonstrate the prediction accuracy. We can observe that the predicted motion of occupants is the same trend as the actual occupant motion. By combining profiles of six rooms, the daily occupant motion profile for the whole house can be estimated.

TABLE III: Prediction Accuracy Comparison with SVM

Machine Learning	MAPE			RMSE		
	Max	Min	Avg	Max	Min	Avg
ELM	0.23	0.10	0.15	29.37	10.92	20.30
SVM	0.34	0.14	0.20	33.75	15.72	23.14
Imp.(%)	31.20	0.50	14.83	30.53	3.32	14.60

TABLE IV: Energy cost saving and energy peak reduction

	Energy Cost Saving(%)			Energy Peak Reduction(%)		
Area	**Max**	**Min**	**Avg**	**Max**	**Min**	**Avg**
25 m^2	83.19	11.59	43.60	16.44	0	6.08
30 m^2	86.26	11.59	48.37	18.30	1.43	9.07
35 m^2	88.46	17.26	51.94	23.31	1.76	15.20
40 m^2	90.10	27.81	51.92	25.32	2.01	16.82
45 m^2	91.38	24.19	49.83	25.32	4.37	17.12
50 m^2	92.41	19.84	45.93	25.32	13.04	18.19

C. Energy Profile Extraction

Fig. 5 illustrates the 24-hour load forecasting results using our proposed method and SVM respectively. It clearly indicates the energy demand between different days varies but our proposed method can accurately capture the peak time of the energy demand. To verify the forecasting accuracy, the proposed online sequential ELM is compared with SVM using MAPE and RMSE, which are shown in Table III. Our proposed sequential ELM forecasting method is 14.83% and 14.60% average improvement comparing to SVM in both MAPE and RMSE. Based on such energy demand prediction, we can effectively utilize the solar energy allocation to reduce the peak demand.

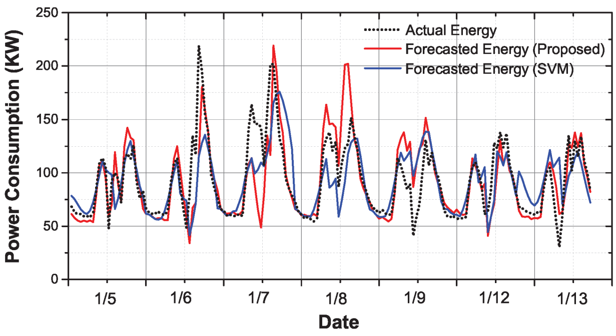

Fig. 5: Energy forecasting with comparison of SVM

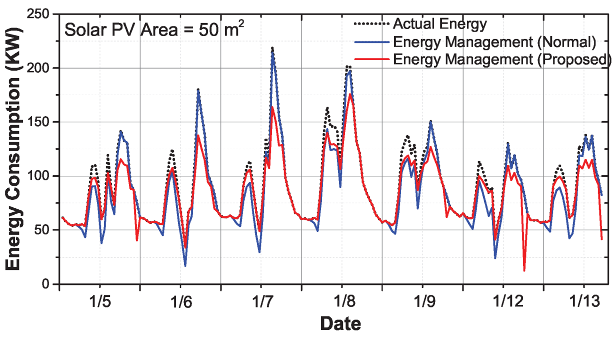

Fig. 6: Demand response with peak demand reduction

D. Energy and Peak Reduction

As mentioned above, it is crucial to reduce the peak energy demand to save cost and maximize the benefit of solar energy from user perspective. Fig. 6 shows the peak reduction based on our proposed method and static energy allocation method respectively. It indicates that our method achieved a lower standard deviation of energy profile from main electricity power-grid than that of static method with more flat curve. The reduced peak loads with various solar PV areas are shown in Table IV. It also shows that our method can perform peak load reduction from 6.08% to 18.19% with various solar PV area, which helps utilize the solar energy to have around 50% cost savings.

VI. Conclusion

In this paper, based on a distributed real-time data analysis, a solar energy allocation to reduce peak load of electricity power-grid is developed for smart building. The distributed real-time data analysis considers both occupant profile and energy profile using a fast machine learning engine running on smart-gateway network without linkage to cloud. Experiment results show that the developed distributed real-time data analytics is 14.83% more accurate than the traditional support vector machine method. Compared to the static prediction, the short-term load prediction can achieve 51.94% more energy saving with 15.20% more peak load reduction.

References

[1] D. J. Cook, J. C. Augusto, and V. R. Jakkula, “Ambient intelligence: Technologies, applications, and opportunities,” *Pervasive and Mobile Computing*, vol. 5, no. 4, pp. 277–298, 2009.

[2] Q. Cheng, J. Yao, H. Wu, S. Chen, C. Liu, and P. Yao, “Short-term load forecasting with weather component based on improved extreme learning machine,” in *IEEE CAC*, 2013.

[3] B. A. Hoverstad, A. Tidemann, H. Langseth, and P. Ozturk, “Short-term load forecasting with seasonal decomposition using evolution for parameter tuning,” *Smart Grid, IEEE Transactions on*, vol. 6, no. 4, pp. 1904–1913, 2015.

[4] H.-T. Yang, J.-T. Liao, and C.-I. Lin, “A load forecasting method for hems applications,” in *IEEE POWERTECH*, 2013.

[5] H. Huang, Y. Cai, H. Xu, and H. Yu, “A multi-agent minority-game based demand-response management of smart buildings towards peak load reduction,” *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*, vol. PP, no. 99, pp. 1–1, 2016.

[6] J. Wang, K. Li, Q. Lv, H. Zhou, and L. Shang, “Hybrid energy storage system integration for vehicles,” in *ACM/IEEE ISLPED*, 2010.

[7] C. Zhang, W. Wu, H. Huang, and H. Yu, “Fair energy resource allocation by minority game algorithm for smart buildings,” in *IEEE DATE*, 2012.

[8] Y. Cai, S. K. Rai, and H. Yu, “Indoor positioning by distributed machine-learning based data analytics on smart gateway network,” in *IEEE IPIN*, 2015.

[9] G.-B. Huang, Q.-Y. Zhu, and C.-K. Siew, “Extreme learning machine: theory and applications,” *Neurocomputing*, vol. 70, no. 1, pp. 489–501, 2006.

[10] H. Huang, Y. Cai, and H. Yu, “Distributed-neuron-network based machine learning on smart-gateway network towards real-time indoor data analytics,” in *IEEE DATE*, 2016.

[11] N.-Y. Liang, G.-B. Huang, P. Saratchandran, and N. Sundararajan, “A fast and accurate online sequential learning algorithm for feedforward networks,” *Neural Networks, IEEE Transactions on*, vol. 17, no. 6, pp. 1411–1423, 2006.

[12] I. Richardson, M. Thomson, and D. Infield, “A high-resolution domestic building occupancy model for energy demand simulations,” *Energy and buildings*, vol. 40, no. 8, pp. 1560–1566, 2008.

[13] N. Ye, Y. Liu, and Y. Wang, “Short-term power load forecasting based on svm,” in *IEEE WAC*, 2012.

[14] S. Barker, A. Mishra, D. Irwin, E. Cecchet, P. Shenoy, and J. Albrecht, “Smart*: An open data set and tools for enabling research in sustainable homes,” *SustKDD, August*, vol. 111, p. 112, 2012.

[15] Pricing strategy for new hampshire electric co-op. [Online]. Available: http://www.oca.nh.gov/Advisory%20Board/ArchivedMinutes/20150727Mtg/NHEC%20Presentation%20re%20AMI%20DP%20Prepaid%207-27-15.pdf