Improving the Prediction Accuracy of Building Energy Consumption using Location of Occupant

−A Case Study*

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***Abstract*—On the one hand, energy consumption forecasting in buildings is of great practical interest due to the large amount of energy that is consumed in buildings and therefore the big energy saving potential. Improving the prediction accuracy has attracted more and more attentions in recent years but still remains an open question. On the other hand, recent advances in technology has provided various economically affordable ways to obtain the location of the occupant. In this work, we focus on how to improve the prediction accuracy of building energy consumption using location of occupant. Three major contributions have been made. First, we formulate the energy consumption prediction problems as Markov decision processes. Second, we develop a platform including a lab, an apartment, and one occupant. The location of the occupant as well as the energy consumption in the lab and the apartment are monitored in the platform. Third, we show that the prediction accuracies of the energy consumption of both the buildings and the occupant can be improved using the location of the occupant. We hope that this work sheds some light on improving the energy efficiency of buildings in the near future.**

Keywords—Smart building; energy consumption forecasting; localization of occupant; platform

I. INTRODUCTION

Nowadays, buildings account for a large proportion of the total energy consumption and carbon emission worldwide. In China, 35% of the primary energy is consumed in buildings [1]. The forecasting of energy consumption in buildings is therefore significant in order to achieve the aim of energy conservation and reducing environment impact.

Traditional methods related to building energy forecasting can be divided into three main categories, including engineering methods, statistical methods and artificial intelligence methods [2]. The engineering methods are usually using physical principles to calculate thermal dynamics and energy behavior of the whole building [3-5]. The statistical models are widely used to predict the energy consumption in buildings such as the regression model [6] and the Auto Regressive Moving Average (ARMA) method [7]. Generally, the most widely used artificial intelligence methods for building energy forecasting are artificial neural network (ANN) [8-9] and Support Vector Machines (SVMs) [10-11]. The hybrid prediction approaches, such as PSO-ANN [12] and PSO-RBF [13] are also proposed to improve the prediction accuracy of building energy in recent years. However, each model mentioned above has its own disadvantages. The engineering models are usually difficult to perform due to high complexity and lack of input information, such as the weather. Generally, the regression models do not accurately reflect the hourly or sub-hourly energy demand. They are best suited for predicting the average consumption over longer periods such as days or months. The time series models such as ARMA are usually based on the assumption that energy use in buildings is periodic. The artificial intelligence methods also present a number of drawbacks and inconvenience such as difficult parameterization, non-obvious selection of variables and over-fitting. Therefore, improving the prediction accuracy of building energy is still an open question.

Building energy greatly depends on occupants [14] together with their energy use behaviors [15-16]. For most people, they usually travel between several fixed buildings every day. For example, an office worker usually commutes between home and the office building every weekday. In this paper we focus on a case study to explore whether the prediction accuracy of building energy can be improved with the location of occupant used. Two topics are considered in this paper, one is the value of location on improving prediction accuracy of the energy consumption of the occupant, and the other one is the value of location on improving prediction accuracy of the energy consumption of buildings.

There exist several difficulties for us to conduct these topics. First, people usually stay together in the same building and several people share an office or a room, which makes it difficult to distinguish the energy use of one occupant from the amount of others. Second, the energy use behaviors of one occupant are influenced by multi-factors, including climate, social-psychology, living habits etc. Still, there is no proper model available to describe the relationship between them. Third, there are some correlations between the location of one occupant and the appliances using, however, there are no causal effects.

Nowadays, building sensing technologies are economically affordable to collect energy use and location of an occupant,

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which makes it possible to derive a data-driven model to predict the energy consumption. Three major contributions are made in this paper. First, we formulate the energy consumption prediction problems as Markov decision processes. Second, we build a platform including a lab, an apartment and one occupant. The location as well as the energy consumption of the occupant are monitored. Third, we show that the prediction accuracy of the energy consumption of both the occupant and buildings can be improved using the location of the occupant.

The reminder of this paper is organized as follows. In Section II, two Markov decision processes are formulated to predict the energy consumption of the occupant with location used and not used. In Section II, a platform including a lab, an apartment and one occupant is built to monitor the energy consumption as well as the location of the occupant. In Section IV, a suboptimal policy is given to solve the Markov decision problems. In Section V, we perform a series of experiments to demonstrate that the prediction accuracy of the energy consumption of both the occupant and the buildings can be improved using the location. Finally, we present our conclusion in Section VI.

II. PROBLEM FORMULATION

In this section, we aim to derive a data-driven model to predict the short-term energy consumption of one occupant in buildings based on the historical energy use data. Since an occupant usually travels between several buildings every day, M buildings are considered in the formulation. For simplicity, each day is equally discretized into N time slots. In order to explore whether the location of the occupant will contribute to the improvement of the prediction accuracy, two Markov decision processes are modeled with the location used and not used respectively.

P1) *if the location of the occupant is not available, the problem to predict the energy consumption of the occupant can be formulated as a finite-stage Markov decision process.*

System States, Actions, and Dynamics: the state of the system is defined as $S_t = E_{t-1}$, where E_{t-1} represents the average energy consumption of the occupant during time slot $t-1$. At the beginning of time slot t , the action A_t is performed to predict the energy consumption $\hat{E}_t$ of the occupant during time slot t. Since at the end of time slot *t*, the energy consumption of the occupant during that period is known, the state transition at time *t* is deterministic, which is

$$S_{t+1} = E_t \tag{2.1}$$

Cost Function: the one-step cost function is defined as the prediction error of the energy consumption at each time slot, which is evaluated at the end of that period.

$$C_t(S_{t+1,}A_t) = \left|\hat{E}_t - E_t\right| \tag{2.2}$$

Therefore, the multi-stage Markov decision problem to predict the energy consumption of the occupant without location can be written as

$$\begin{aligned} \min_{\pi=(d_1,d_2,d_{3,\dots,}d_T)} \quad & \sum_{t=1}^{T} E\left[C_t(S_{t+1},A_t)\right] \\ s.t. \quad & \hat{E}_t = d_t(S_t) \\ & S_{t+1} = E_t \end{aligned} \tag{2.3}$$

P2) *if the location of the occupant is utilized in the prediction process, the problem is also formulated as a finite-stage discrete Markov decision problem.*

System Sates, Actions and Dynamics: the system state S_t is comprised of the energy consumption E_{t-1} and the location L_{t-1} of the occupant at time slot $t-1$. At the beginning of time slot *t*, the action A_t is performed to predict the location $\hat{L}_t$ and then the energy consumption $\hat{E}_t$ of the occupant during time slot t .Since at the end of time slot *t*, the energy consumption and the location of the occupant during that period is known, the state transition at time *t* is deterministic, which is

$$S_{t+1} = \left[E_t, L_t\right] \tag{2.4}$$

Decision Space: we assume that the occupant travels between *M* buildings every day. Since it usually takes some time for the occupant to travel from one place to another, some constraints exist on the prediction of the location. For instance, if $L_{t-1} = i$, then

$$\hat{L}_t \in \left\{ j \mid j \in \{1,2,\dots,M\} \setminus P \right\} \tag{2.5}$$

where if $j \in P$, it will take the occupant more than one time slot to travel form building i to building j .

Cost Function: the prediction error of the energy consumption during time slot *t* is defined as the one-step cost function, which is evaluated at the end of each period.

$$C_t(S_{t+1,}A_t) = \left|\hat{E}_t - E_t\right| \tag{2.6}$$

The problem to predict the energy consumption based on the location of the occupant can be written as

$$\begin{aligned} \min_{\pi=(d_1,d_2,d_{3,\dots,}d_T)} \quad & \sum_{t=1}^{T} E\left[C_t(S_{t+1},A_t)\right] \\ s.t. \quad & \left[\hat{E}_t,\hat{L}_t\right] = d_t(S_t) \\ & \hat{L}_t \in \left\{ j \mid j = \{1,2,\dots,M\} \setminus P \right\} \\ & S_{t+1} = \left[E_t, L_t\right] \end{aligned} \tag{2.7}$$

III. PLATFORM

In order to collect the energy use data and the location of one occupant, a platform including a lab, an apartment and a graduate student is built as Fig. 1.

The electricity appliances in our experiments can be divided into three categories. The first category is about the central air-conditioning. Considering the real-time power of the central air-conditioning is hard to be supervised directly, a Netatmo weather station is installed in the lab to measure real-time environmental parameters, which can be used to estimate the power of the air-conditioning. Since the energy consumption of the central air-conditioning is commonly shared, this part is not considered yet in this paper. However, we may take it into account in our future work. The second category of appliances related to the occupant are the lights. A luminance sensor is installed beside each light to gather the light's state (on or off). Then based on the on-off state of the lights along with its rated power parameters, we can approximate the real-time power of the lights. The third category of appliances is the plug-in load, including the chargers, the lamp, the desktop, the laptop, the hair dryer, etc. This part of loads could be measured through a power meter.

Except for the energy use data, another category of information monitored is the location of the occupant. A GPS location device with a SIM card inside is used to distinguish the individual's location from the lab to the dorm. The real-time location information is download from a website provided by the product manufacturer.

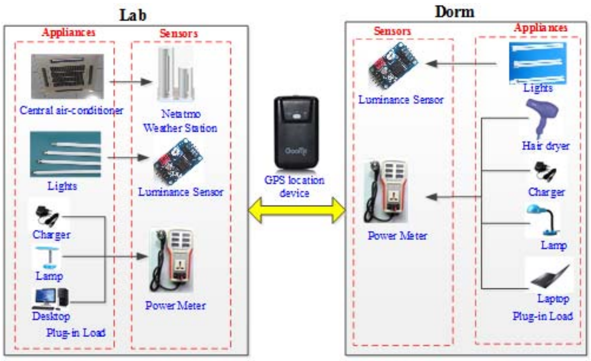

Fig. 1. Platform

IV. SOLUTION METHODS

The Markov decision problems proposed in Section II are difficult to solve, since little information is available to obtain an absolutely accurate prediction. In this section, a suboptimal policy is given to offer a quite good prediction of the energy consumption of the occupant.

Considering the historical energy use data of the occupant, days are classified into seven "categories", including Monday, Tuesday, Wednesday, Thursday, Friday, Saturday and Sunday. The historical energy use data as well as the location of the occupant are grouped according to the "categories" of the days. A policy to predict the energy consumption of the occupant is derived from the grouped data.

A. A policy for model P1

In model ***P1***, the location of the occupant is ignored, the historical energy use data of the occupant are maintained in 7 groups according to the "categories" of days. For instance, the third group stores the historical energy use data on Wednesday.

Based on the grouped energy use data of the occupant, a statistical model is formulated. The mean and standard of the energy consumption of the occupant at time slot t of the i-th (i=1, 2, 3,…,7) "category" of days are computed as

$$\mu_t^i = \sum_{k=1}^{N_i} E_t^i(k) / N_i \tag{4.1}$$

$$\sigma_t^i = \sqrt{\sum_{k=1}^{N_i} \left(E_t^i(k) - \mu_t^i\right)^2 / (N_i - 1)} \tag{4.2}$$

The minimum and the maximum energy consumption at time slot t of the i-th (i=1, 2, 3,…,7) "category" of days are

$$m_t^i = \min_{k=1,2,\dots,N^i} E_t^i(k) \tag{4.3}$$

$$M_t^i = \max_{k=1,2,\dots,N^i} E_t^i(k) \tag{4.4}$$

where N^i is the number of the i-th "category" of days in the past. E_t^i is the energy consumption at time slot t of the i-th "category" of days.

Since no prior knowledge about the energy behavior of the occupant is available, a truncated Gaussian distribution with mean μ_t^i and variance $\left(\sigma_t^i\right)^2$ is used to describe the stochastic characteristics of the energy consumption at time slot t. The Gaussian distribution is both bounded below and above with m_t^i and M_t^i. The predicted energy consumption $\hat{E}_t^i$ at time slot t of the i-th "category" of days is

$$\hat{E}_t^i \sim N\left(\mu_t^i, \left(\sigma_t^i\right)^2\right),\ m_t^i \le \hat{E}_t^i \le M_t^i \tag{4.5}$$

B. A policy for model P2

In order to derive a policy for model ***P2***, the historical energy use data is divided into 7×2 groups considering both the "categories" of days as well as the location of the occupant. For instance, the (3×1) group stores the historical energy use data on Wednesday when the occupant is present in the apartment and the (3×2) group stores the historical energy use data on Wednesday in the lab.

Similarly, the mean and standard of the energy consumption of the occupant at time slot t are computed as

$$\mu_t^{(i,j)} = \sum_{t=1}^{N_t^{(i,j)}} E_t^{(i,j)}(k) / N_t^{(i,j)} \tag{4.6}$$

$$\sigma_t^{(i,j)} = \sqrt{\sum_{t=1}^{N_t^{(i,j)}} (E_t^{(i,j)}(k) - \mu_t^{(i,j)})^2 / (N_t^{(i,j)} - 1)} \tag{4.7}$$

The minimum and the maximum energy consumption of the occupant at time slot t are computed as

$$m_t^{(i,j)} = \min_{k=1,2,\dots,N_t^{(i,j)}} E_t^{(i,j)}(k) \tag{4.8}$$

$$M_t^{(i,j)} = \max_{k=1,2,\dots,N_t^{(i,j)}} E_t^{(i,j)}(k) \tag{4.9}$$

Where i represents the i-th "category" of days. j denotes the location of the occupant. If $j=1$, the occupant is in the apartment and if $j=2$, the occupant is in the lab. $N_t^{(i,j)}$ denotes the number of days on the i-th "category" of days when the occupant is present at different locations at time slot t. $E_t^{(i,j)}$ is the energy consumption of the occupant at different locations at time slot *t*.

Similarly, a truncated Gaussian distribution with mean $\mu_t^{(i,j)}$ and variance $\left(\sigma_t^{(i,j)}\right)^2$ is used to approximate the stochastic characteristics of the energy consumption of the occupant at time slot *t*. The Gaussian distribution is both bounded below and above with $m_t^{(i,j)}$ and $M_t^{(i,j)}$.

In model ***P2***, the location of the occupant is predicted and then the predicted location is employed in the prediction process of the energy consumption. We use a time-variant Markov chain to describe the location transition of the occupant at each time slot. Based on the historical location data, a Markov chain P^t, of size 3×3, can be formulated to describe the location transition of the occupant. The transition probability P_{ij}^t of the occupant transferring form place *i* to place *j* at time slot *t* is estimated as

$$P_{ij}^t = N_{ij} / \sum_l N_{il} \tag{4.10}$$

where N_{il} represents the frequency that the individual occupant transferring from place *i* to place *l* at time slot *t*.

Therefore, a statistical model to predict the energy consumption $\hat{E}_t^i$ of the occupant at time slot *t* based on location can be written as

$$\hat{E}_t^i \sim \sum_{k=0}^{3} P_{kj} N\left(\mu_t^{(i,j)}, \left(\sigma_t^{(i,j)}\right)^2\right) \quad m_t^{(i,j)} \le \hat{E}_t^{(i,j)} \le M_t^{(i,j)} \tag{4.11}$$

where *k* represents the current location of the occupant and P_{kj} denotes the location transition probability from building *k* to building *j* at next time slot.

C. *Performance Metrics*

In order to evaluate the value of location on the prediction accuracy of the energy consumption of both the occupant and the buildings, two evaluation metrics ***M1*** and ***M2*** are proposed in this subsection.

M1)*the average prediction error of the energy consumption of the occupant for T time slots is shown in Fig. 2.*

The performance indicator can be written as

$$M_1(\%) = \frac{\sum_{t=1}^{T} \left|\hat{E}_t - E_t\right|}{\sum_{t=1}^{T} E_t} \tag{4.12}$$

where $\hat{E}_t$ and E_t are the predicted and the actual energy consumption at time slot *t*, respectively.

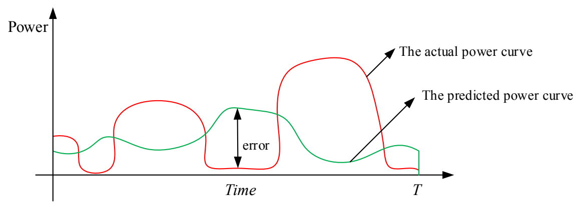

Fig. 2. The average prediction error of the energy consumption of the occupant

M2)*the average prediction error of the energy consumption of buildings is shown in Fig. 3.*

The prediction error of the energy consumption in the apartment and in the lab can be written as (4.13) and (4.14).

$$M_2(\%) = \frac{\sum_{t=1\sim T_1, T_5\sim T} \left|\hat{E}_t - E_t\right|}{\sum_{t=1\sim T_1, T_5\sim T} E_t} \tag{4.13}$$

$$M_2(\%) = \frac{\sum_{t=T_2\sim T_3, T_4\sim T_5} \left|\hat{E}_t - E_t\right|}{\sum_{t=T_2\sim T_3, T_4\sim T_5} E_t} \tag{4.14}$$

where $\hat{E}_i$ is the predicted energy consumption at time slot *t*. E_t is the actual energy consumption at time slot *t*.

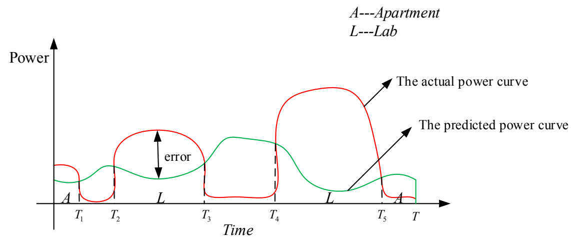

Fig. 3. The average prediction error of the energy consumption of buildings

V. Experiment Results

The energy use data and the location of a graduate student is collected during 2015/6/9~2015/6/14, 2015/6/18~2015/6/28, and 2015/8/31~2015/9/13 through the platform. In our experiments, a whole day (24h) is equally divided into $N = 288$ time slots, each corresponding to a 5 minutes interval. The average power value during each time slot is used to represent the energy use of the graduate student. The energy use of the graduate student on 2015/9/1 is as Fig. 4.

In this section, a series of experiments are conducted to explore these two topics: ***E1)*** the value of location on the prediction accuracy of the energy consumption of the occupant; ***E2)*** the value of location on the prediction accuracy of the energy consumption of the buildings.

A. *The location transition of the occupant*

As mentioned in Section IV, the location transition of the occupant can be modeled as a homogeneous Markov chain. The location transition probability at each time slot is computed using (4.10). For instance, the location transition probability matrix of the occupant at 8:00 A.M. is as TABLE I.

TABLE I. The location transition of the occupant at 8 A.M.

	O	**A**	**L**
O	1	0	0
A	0.118	0.882	0
L	0	0	1

Where "**A**" represents the apartment, "**L**" represents the lab and "**O**" represents the other places not considered in this paper.

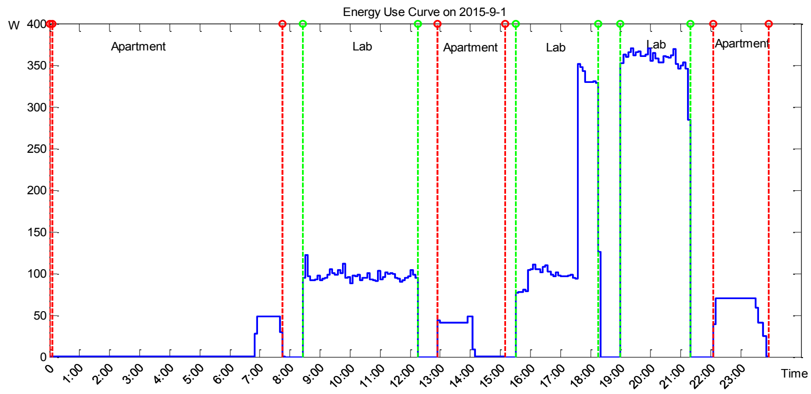

Fig.4 The energy use curve on 2015/9/1

B. *The value of location in Topic E1*

In this subsection, two sets of experiments are conducted to predict the energy consumption of the graduate student from 2015/9/7 to 2015/9/13. In one set of experiments, the location of the occupant is ignored and in the other one the location is used. The actual and the predicted energy use curves on 2015/9/8 (Tue.) and 2015/9/10 (Thu.) are shown in Fig. 5 and Fig. 6.

The prediction error based on the evaluation metric ***M1*** of each predicted day is computed, as TABLE II. TABLE II shows that the average prediction errors of the energy consumption of the occupant are apparently reduced with the location used. Therefore, a preliminary conclusion is obtained that the location of is useful in improving the prediction performance of the energy consumption of the occupant.

TABLE II. The prediction error of the energy consumption of the occupant

Category of Days	**Date**	**M1 (%)**	
		Location Not Used	***Location Used***
1	2015/9/7	22.6	19.8
2	2015/9/8	58.9	29.6
3	2015/9/9	48.1	21.0
4	2015/9/10	53.8	22.1
5	2015/9/11	60.0	36.6
6	2015/9/12	49.0	21.8
7	2015/9/13	52.8	35.6

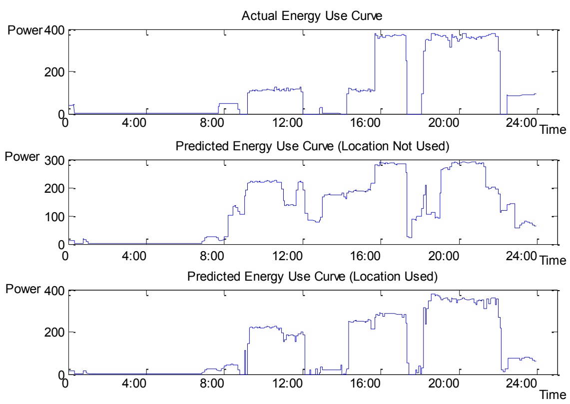

Fig. 5. The actual energy use curve and the predicted energy use curves (Location Used or Location Not Used) on 2015/9/8

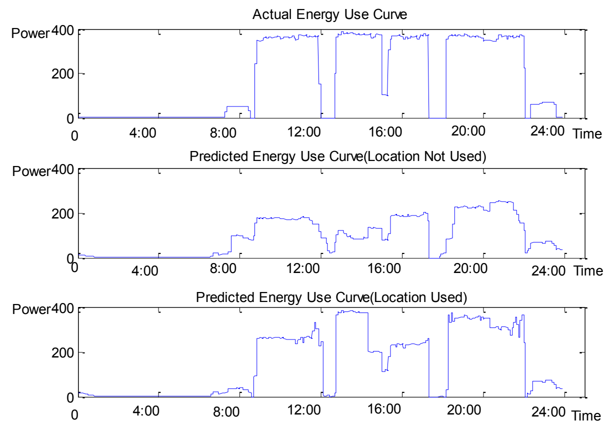

Fig. 6. The actual energy use curve and the predicted energy use curves (Location Used or Location Not Used) on 2015/9/10

C. *The value of location in Topic E2*

In this subsection, we aim to explore whether the prediction accuracy of the energy consumption related to the buildings can be improved using the location of the occupant. Similarly, two sets of experiments are conducted to predict the energy consumption of the occupant in the apartment and in the lab from 2015/9/7 to 2015/9/13. One is without the location, and the other one is with the location used. Figure 7 and Figure 8 shows the actual and the predicted energy use curves on 2015/9/7 and 2015/9/12. The blue area represents energy consumption of the occupant in the apartment and green area represents the energy consumption in the lab.

The average prediction error of the energy consumption of the occupant in the apartment and in the lab are computed using the evaluation metric ***M2***. The results are shown in TABLE III. TABLE III shows that the average prediction error of the energy consumption both in the apartment and in the lab are apparently reduced on each predicted days except for the day of 2015/9/13. The main reason lies in the prediction error of the location transition probability of the occupant. Another category of experiments is carried out to explain this phenomenon. In the experiments, we assume that the location of the occupant at next time slot is known before the prediction of the energy consumption is performed. The average prediction error in the apartment on 2015/9/13 is 52.4%. Compared with the average prediction error of 57.2%, the prediction accuracy is improved by 5%. Therefore the prediction accuracy of the energy consumption of buildings can be improved as long as the location of the occupant is well utilized.

TABLE III. THE AVERAGE PREDICTION ERROR IN THE APARTMENT

Category of Days	Date	M2 (%) In the apartment		M2 (%) In the lab	
		Location Not Used	*Location Used*	*Location Not Used*	*Location Used*
1	2015/9/7	52.7	33.0	19.3	18.4
2	2015/9/8	142.3	41.5	40.3	25.9
3	2015/9/9	57.6	33.0	41.9	18.8
4	2015/9/10	63.0	43.2	51.8	20.5
5	2015/9/11	136.9	77.7	49.7	35.1
6	2015/9/12	55.1	53.8	50.6	22.1
7	2015/9/13	57.2	57.5	47.6	33.7

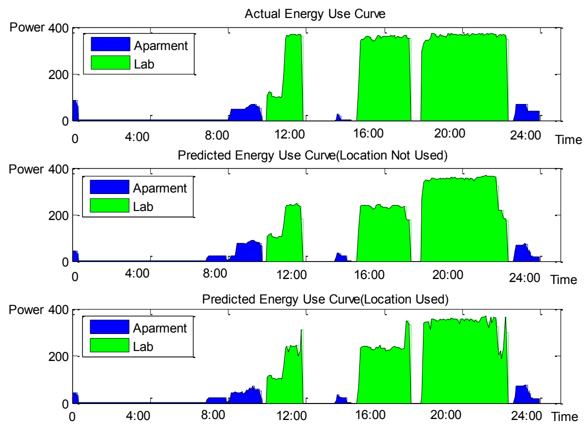

Fig. 7. The actual and the predicted energy use curves on 2015/9/7

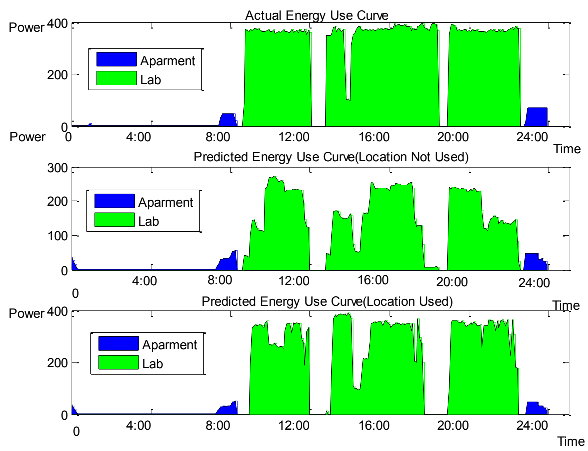

Fig. 8. The actual and the predicted energy use curves on 2015/9/12

VI. CONCLUSION

In this paper, we developed a general framework to improve the prediction accuracy of the energy consumption of buildings using the location of the occupant. A series of experiments are conducted to demonstrate this topic. A preliminary conclusion is obtained that the prediction accuracy of the energy consumption of both the occupant and the buildings can be apparently improved with the location of the occupant is effectively utilized.

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