Situation-based Energy Management System

Seung-Won Lee
Future IT Convergence Lab
LG Electronics Advanced Research Institute
Seoul, Korea
seung.lee@lge.com

Se Heon Choi
Future IT Convergence Lab
LG Electronics Advanced Research Institute
Seoul, Korea
ruben.choi@lge.com

Minkyung Cho
Future IT Convergence Lab
LG Electronics Advanced Research Institute
Seoul, Korea
minkyung.cho@lge.com

Jungsu Lee
Future IT Convergence Lab
LG Electronics Advanced Research Institute
Seoul, Korea
jungsu.lee@lge.com

***Abstract*—Energy related technology such as Smart Grid has become one of the main interests in modern industry. Deciding whether to supply or store energy by predicting the amount of energy consumption rate is the core technology in Smart Gird. In this paper, we present a situation-based prediction (SBP) system that not only utilizes user's usage history data but also makes use of the user's situation that is derived from various sensor data. According to our experiment, situation-based prediction system has about four times better performance compared to the time-based prediction system which solely relies on user's usage history.**

Keywords-situation; context; energy; Bayesian Networks

I. INTRODUCTION

A large number of researches have been done on energy management system. At the initial stage, most of the systems were based on simple rule-based system and have evolved to use some contexts (e.g., location) to predict whether more power will be required or not [1][2].

However, most of these context-aware prediction systems are based on simple sensor data and past usage history. Past usage history is not sufficient to detect unordinary conditions and sensor data can only distinguish simple circumstance unless we draw a meaningful significance from those sensor data.

We anticipate that the next stage of energy management system is to understand the gathered contexts and derives meanings from them. In our system, we call it a situation. One possible way to analyze and derive situation from contexts is to use probabilistic network such as Bayesian networks (BNs), also called belief networks, Bayesian belief networks, which are widely used to model uncertain and complex domains [3]. Our situation-based prediction (SBP) system is based on this Bayesian Network, where a cell phone acting as a main device loaded with BN. Cell phone gathers contexts from itself along with other electronic devices at home or office (e.g., TV, light, PC) and uses these contexts as evidence for running Bayesian Network [4]. The main idea of situation based prediction system is to keep track of user's energy consumption rate based on user's situation. We believe recording and analyzing situation can eventually tell user's life pattern and adjust the energy management system to specific user or group of users.

This paper is about our research and development of situation-based prediction algorithm for energy management system and its potential benefit compared to other energy prediction systems.

The organization is as follows: Section 2 starts with the definition of the term "Situation". Section 3 explains the process of gathering and utilizing the usage history data associated with situation. Section 4 covers retrieval and application of feedback data. Section 5 gives a short description of the experiment, and Section 6 presents the advantage of situation-based prediction system. Lastly, we present our conclusion along with possible future works.

II. DEFINITION OF SITUATION

We define situation as interpretation of various sensor data. Sensor can be any device that can give information (context). For example, heater and air conditioner can tell us the temperature of that area. Motion detector, light sensor can present the location of the users in that area. Situation is derived by analyzing these raw sensor data.

One sample situation can be "Sleeping at room". This situation can be derived by using time, light sensor, and other electronic equipments in room. If light sensor and other electronic equipments are off and the time is late at night, we can assume that the user is sleeping or about to get to sleep. In our system, we classified 5 different situations; Sleeping, Watching TV, Eating, Working, and Resting. In addition, the system detects user movement to decide whether to derive the situation or not, since all 5 situations we classified occur while user staying in one position. The sensors we have used to derive situation were personal cell phones, TVs, lights, and personal computers.

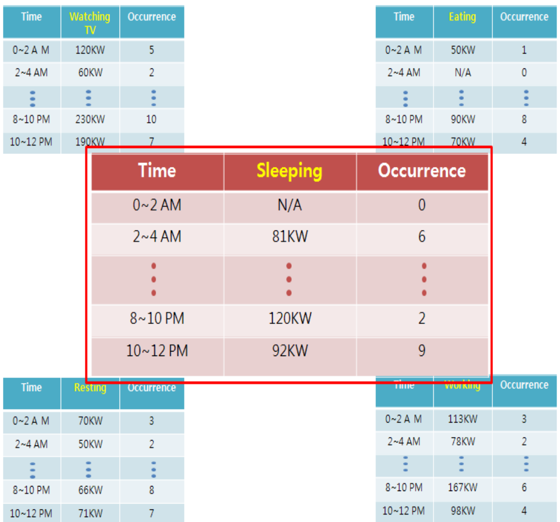
III. RECORDING AND PREDICTING ENERGY CONSUMPTION RATE

SBP records user's energy consumption rate every two hours. However, if the system detects that user is moving, it

 ISBN: 978-1-61208-164-9

does not react until the user's movement is finished. We defined moving as a movement from one isolated place to another isolated place. For instance, moving from a living room to a dining room would be considered as moving, whereas a movement within the living room is not. When recording user's energy consumption rate, SBP first derive the current situation in probabilistic matter by running the Bayesian network. A sample result of running the network can be: Sleeping (87%), Watching TV (50%), Eating (10%), Working (15%), and Resting (60%). We only record the highest probable situation which would be "Sleeping" in this case and the amount of consumed energy at that point. In order to derive reliable data, we only record the situation and the consumed energy amount only if the probability is higher than 75%. Once a pair of situation and amount of consumed energy data is collected, we store these data to the database which is composed of time slot, average amount of consumed energy and the number of occurrence. Each situation has its own database table. (Fig. 1)

The number of occurrence data is used to update the average amount of consumed energy and to apply feedback data which will be discussed in Section 5. When an update occurs, we increase the number occurrence by one, and update the average amount of consumed energy. (Fig. 2)



Time	Watching TV	Occurrence
0~2 A M	120KW	5
2~4 AM	60KW	2
⋮	⋮	⋮
8~10 PM	230KW	10
10~12 PM	190KW	7

Time	Eating	Occurrence
0~2 A M	50KW	1
2~4 AM	N/A	0
⋮	⋮	⋮
8~10 PM	90KW	8
10~12 PM	70KW	4

Time	Sleeping	Occurrence
0~2 AM	N/A	0
2~4 AM	81KW	6
⋮	⋮	⋮
8~10 PM	120KW	2
10~12 PM	92KW	9

Time	Resting	Occurrence
0~2 A M	70KW	3
2~4 AM	50KW	2
⋮	⋮	⋮
8~10 PM	66KW	8
10~12 PM	71KW	7

Time	Working	Occurrence
0~2 A M	113KW	3
2~4 AM	78KW	2
⋮	⋮	⋮
8~10 PM	167KW	6
10~12 PM	98KW	4

Figure 1. Database table for each situation

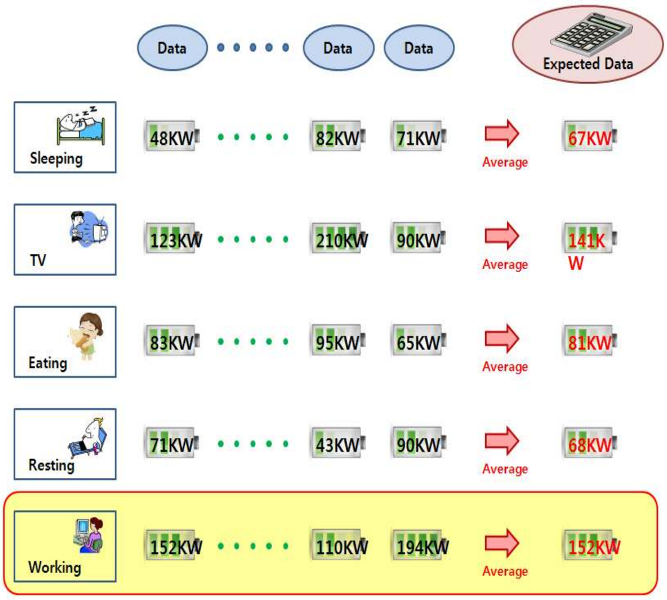


Figure 2. Calculating average amount for each situation

One subtle issue in the system is to decide when to derive a situation. As we mentioned above, the SBP detection occurs every two hours, when no user movement is found. We believe energy consumption rate varies if user moves from place to place. For example, move to dining room to watch TV, move to kitchen to cook, etc. Therefore, if user movement is detected, the system waits until user settles at certain place. However, if the system urgently needs the energy prediction rate, it forecasts the next possible situation by comparing the "Occurrence" field of each situation database. For example, if current time is 2:00 AM, the system retrieves the occurrence field of "2~4 AM" from each database and selects the one that has the highest number. Since the main object of our experiment was to compare situation-based prediction to time-based prediction, the system tries to detect the movement of the user every two hours. We are also considering deriving a situation whenever a user movement is detected regardless of time. In this way, the size of the situation database will decrease by one twelfth but may require more updates if user frequently moves from place to place.

Once the database is filled with enough data, the system utilizes these data to predict user's energy consumption rate. We believe the prediction accuracy increases as the size of the database grows and converges at certain point. Discovering the convergence point would require an experiment in real world. As for now, we gathered a month period data before prediction.

Following are the two steps that SBP uses to predict the amount of energy consumption rate.

1) SBP first runs the Bayesian network and derives the current situation by picking the highest probable situation. Since the probability threshold is set to 75%, SBP does not give its prediction value if the probability is less than 75%.

 ISBN: 978-1-61208-164-9

When a tie occurs on situations, although it rarely happens, we randomly pick one situation.

2) Once a situation is selected, the system retrieves the database of the selected situation, and gets the average amount of consumed energy of the current time slot. For example, if current time is 12:30AM and selected situation is “Sleeping”, the system retrieves energy consumption data of “0-2 AM” from “Sleeping” database for its final prediction rate.

IV. APPLYING FEEDBACK DATA

As we mentioned before, SBP is based on probabilistic network such as Bayesian Network and is used to discover user’s current situation. In addition to discovering situation, we built a separate database that keeps track of energy consumption rate. Once the system gives its prediction, it observes the actual amount of consumed energy. The difference between the actual amount of consumed energy and the predicted amount is used as the feedback data, and affects future prediction.

In our system, there are two kinds of feedback data, positive feedback and negative feedback. We call it a positive feedback when the predicted consumption rate is higher than actual consumption rate and negative feedback is the opposite where predicted amount is less than the actual one.

	“Sleeping”	“Watching TV”	“Eating”	“Working”	“Resting”
12-2PM	N/A	520KW	78KW	90KW	45KW
2-4PM	N/A	~~550KW~~ 539KW	110KW	85KW	40KW
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
10-12PM	24KW	470KW	N/A	99KW	30KW

Figure 3. Applying Feedback Data

After receiving the feedback data, we reflect this data to our future prediction by dividing the difference between the predicted amount and the actual amount by the number of data we have used to draw our prediction (# of occurrence). For example, let’s say the current situation is “Watching TV” and the received feedback is +110 KW (predicted amount = 550 KW, actual amount = 440 KW, number of occurrence = 10). We divide 110 KW by 10 which give us 11 KW and then subtract this number from our prediction amount. In other words, our next prediction amount of that situation at that time slot will be 539 KW instead of 550 KW while the number of occurrence remains as 10. (Fig 3)

The feedback data we have mentioned above are only used to modify the prediction amount of consumed energy. In addition to that, we also allow user to give feedback to the derived situation. The Situation-Based Prediction system makes it prediction assuming the derived situation is accurate. However, the accuracy of the Bayesian Network is not always 100% and needs to adjust its network to a specific user or a group of users. Since cell phone is working as a main device by actually running the Bayesian Network. Whenever a situation is derived (once every two hour), the cell phone outputs the resulting situation and asks whether the situation is correct or not. This feedback data is only used to reinforce the Bayesian Network.

V. EXPERIMENT

At this point, our experiment is being done in a simulation environment. The simulator consists of a dining room, four living rooms, and two bath room where each room equipped with TV, light, and personal computer. The experiment is targeted to verify two main issues. First is to check the competitiveness of our Bayesian Network by analyzing the accuracy of the derived situation. The other issue is to see whether SBP indeed gives better performance compared to other energy prediction systems. Unfortunately, it is hard to present the results without experimenting in real environment; however, according to our simulation SBP does have high accuracy when the derived situation is accurate. The details of our simulation are following. We built a simulator that simulates user’s daily home life. User randomly acts one of 6 situations; Sleeping, Watching TV, Eating, Working, Resting, and Moving. As we mentioned before, when “Moving” occurs, the system waits until user enters a certain space and detects one of the situations. We recorded 2 hour based energy consumption rate for 30 days in simulator environment. Fig. 4 shows the results of the experiment.

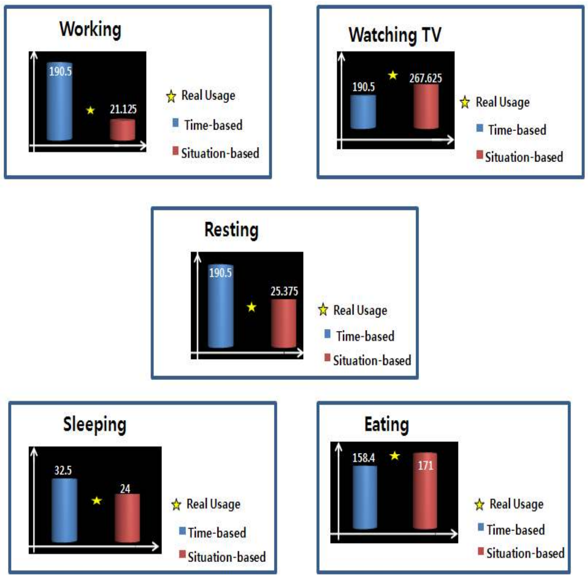


Figure 4. Comparison between Time-based prediction and Situation-based prediction.

For comparison, each graph presents average prediction value of time-based system, situation based system, and the actual usage rate of the user. Situation-based prediction system gave much better performance when multiple situations occur in certain time slot. For instance, if user either watches TV or sleeps in certain time slot, there is a big difference in consumption rate between these two situations and time-based prediction cannot reflect this circumstance.

In average, time-based system had 54% average error rate when multiple situations occur in certain time slot whereas, situation-based system had only 12% average error rate. We need to acknowledge that simulation was run upon assumption that situation was accurately derived at all time. The accuracy of our Bayesian Network needs to be measured in real environment, and for now we leave it as our future work.

VI. ADVANTAGE OF SITUATION-BASED PREDICTION

A. *Accuracy*

While most of the modern energy management systems rely on past energy consumption history, SBP tracks history by analyzing user's situation. Energy consumption happens when activity occurs and situation is one of the best ways to predict user's activity. We are certain that SBP's accuracy is at least higher than the system that solely relies on past usage history, since SBP is also based on history data. The biggest difference is that, SBP segments these usage data and retrieves the most relevant history.

B. *Specialization*

As we mentioned earlier, SBP is based on probabilistic network such as Bayesian Network. One of the biggest strength of Bayesian Network is that it evolves as it receives feedback data from users. There are plenty of ways to receive feedback data from users directly or indirectly. However, we will not get into details of receiving and analyzing feedback data of Bayesian Network since it is beyond the scope of this paper. The essential point is that SBP keeps evolve as the size of the usage history data grow, and as it receives more feedback data from users. In other words, SBP evolves to get customized for a specific user or a specific group of people.

VII. CONCLUSTION AND FUTURE WORKS

In this paper, we presented a Situation-Based Prediction system for energy management. The system is based on Bayesian Network, and derives user's situation in order to associate it with energy consumption rate. We are certain that SBP is more efficient than other energy managing system that solely relies on users' past usage history and is capable of adjusting the system to a specific user or group of users.

SBP is currently targeted for a single user. Our future work will be focused on expanding our SBP to support multiple users in a distributed environment [5]. Each user will use his/her cell phone acting as a main sensor, and share information with one another. The biggest challenge of our future work will be detecting correlation among users. For example, when SBP detects that multiple users are watching TV, it needs to find out whether all of the users are watching the same TV or not. In addition, creating a database that holds individuals' past situation and associating one another to draw a reliable prediction will be the key challenge.

REFERENCES

[1] C. Harris and V. Cahill, "An Empirical study of the potential for context-aware power management," UbiComp 2007: Ubiquitous Computing (2007), pp. 235-252, doi:10.1007/978-3-540-74583-3_14.

[2] R. K. Harle and A. Hopper, "The Potential for Location-Aware Power Management", UbiComp 2008: Ubiquitous Computing (2008), pp. 302-311, doi:10.1145/1409635.1409676.

[3] L. Uusitalo, "Advantages and challenges of Bayesian networks in environmental modelling", Ecological Modelling, vol. 203, No.3-4 (10 May 2007), pp. 312–318.

[4] P. Korpipää, J. Mäntyjärvi, J. Kela, H. Kernen, and E.-J. Malm, "Managing context information in mobile devices", Pervasive Computing, IEEE In Pervasive Computing, IEEE, vol. 2, no. 3, pp. 42–51, doi:10.1109/MPRV.2003.1228526.

[5] G. Pavlin, P. de Oude, M. Maris, J. Nunnink, and T. Hood, "A multi agent systems approach to distributed Bayesian information fusion", INFFUS, vol. 11, no. 3, pp. 267-282, doi:10.1016/j.inffus.2009.09.007.

ISBN: 978-1-61208-164-9