Title	**Integration of BIPV systems and load management**
Author(s)	**Lam, KH; Lee, WK; Lo, EWC; Lai, TM**
Citation	**The International Conference on Electrical Engineering 2009.**
Issued Date	**2009**
URL	**http://hdl.handle.net/10722/133929**
Rights	**Creative Commons: Attribution 3.0 Hong Kong License**

The International Conference on Electrical Engineering 2009

Integration of BIPV systems and load management

K. H. Lam, W. K. Lee, E. W. C. Lo, and T. M. Lai

***Abstract*-- This paper outlines the basics of load management, and highlights the possibility of maximising the contribution from the Building Integrated Photovoltaic (BIPV) power generation. It will also explain the underlying principles of a dynamic modelling approach and its application in supporting the anticipatory control strategy for load shifting.**

For many types of building applications, the load profiles are well matched with the BIPV generation profiles such that the BIPV power source is already acting as the peak clipping device. The application of Building Management Systems (BMS) in load shifting should consider the supply from BIPV system. Secondly, due to the thermal mass of the building, there exists time delay in the response of the power requirement of the HVAC system in the building from the solar radiation data. The BIPV system, on the contrary, is responding almost instantaneously to the solar irradiance. A dynamic BIPV model could be applied in aiding the prediction of the load profile. This paper will outline these aspects of the dynamic model developed as a demonstration of its application.

***Keywords*—Building Integrated Photovoltaic Systems, Building Management Systems, demand side management.**

I. INTRODUCTION

IN developed countries, usually the built environment consumes about 42% - 45% of the total energy demand within the nation [1]. In the European Union there are 160 million buildings taking up over 40% of Europe's energy and generating a similar portion of CO_2 [2]. Therefore energy efficiency within a building has significant potential contribution to sustainable development. And one of the approaches to improve energy efficiency is by means of the building management systems (BMS). This paper outlines the basics of BMS, and hence highlights the possibility of maximising the contribution from the BIPV power generation. The underlining principles are also explained for the dynamic model's application in supporting the BMS anticipatory control strategy for load shifting.

II. LOAD MANAGEMENT

Although embracing a much wider scope of meanings, the two major functions of a BMS are to maintain energy efficiency and occupants comfort. When load management is concerned, there are three important modes of BMS application in automation and control of mechanical and electrical systems:

A. Energy Demand Shedding

This is the process of reducing the overall energy demand of the entire building. The conventional means of achieving demand shedding is by replacing inefficient appliances by energy saving devices. For example the upgrading of traditional lighting and heating ventilation air-conditioning (HVAC) systems with efficient components or even a new and more efficient system. This straightforward means is very cost effective since the energy saved can be very significant. Another way to attain demand shedding is by proper installation of BMS. Although admitting the intricacy in quantifying the amount of energy saving with BMS, Kumar et al. [3] estimated the possible saving for HVAC systems in commercial buildings could be around 20-30%. Since the demand shedding schemes are not time dependent and therefore do not correspond to the load profile (and hence not related to anticipatory control), they could not be related to the dynamic behaviour of grid-connecting BIPV systems which could be applied to support the BMS control strategies.

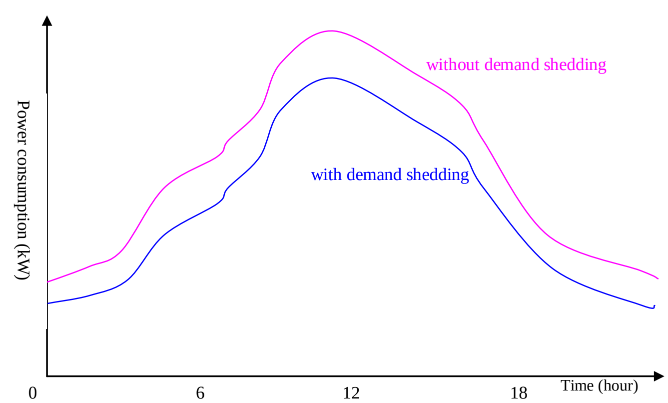

Fig. 1. Example of load profiles with and without demand shedding control strategy.

B. Peak Load Clipping

Peak load clipping, on the other hand, is the reduction of electricity consumption during peak hours. This could be a by-product of energy demand shedding mechanism; or by switching off non-crucial equipment at desire periods. Neither

K. H. Lam and W. K. Lee are with the Department of Electrical & Electronic Engineering, The University of Hong Kong, Pokfulam Road, Hong Kong SAR, China (e-mails: khlam@eee.hku.hk, wklee@eee.hku.hk).

Edward W. C. Lo is with the Department of Electrical Engineering, Hong Kong Polytechnic University, Hung Hom, Hong Kong SAR, China (e-mail: eewclo@inet.polyu.edu.hk).

T. M. Lai is with the School of Business, Macao Polytechnic Institute, Rua de Luis Gonzaga Gomes, Macao SAR, China (e-mail: tmlai@ipm.edu.mo).

of which involves sophisticated control of BMS. Furthermore, it could result in reduction of occupant comfort when peak clipping is the over-riding principle. Hence it is of little research value when the dynamic and temporal characteristics of the BIPV system are under investigation. An example of peak load clipping is shown below:

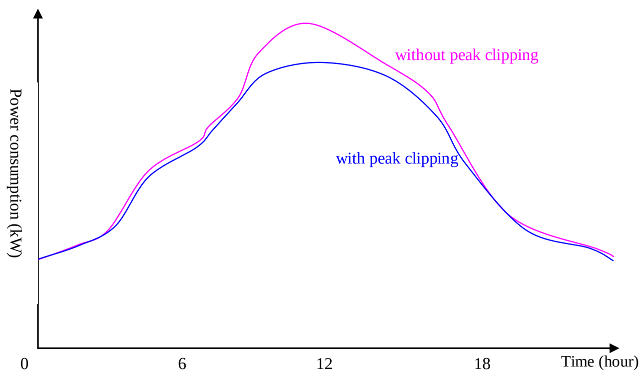

Fig. 2. Example of load profiles with and without peak load clipping control strategy.

C. Load Shifting

In contrast to the above methods, load shifting is the reduction of electricity consumption during peak periods, by means of re-scheduling of some of the controllable equipment [4]. The control process involves sophisticated load profile monitoring, prediction, and then finally decision-making by means of artificial intelligence. The contribution from BIPV systems would then be critical if a certain part of the load is going to be supplied by the energy from the sun. A dynamic model which could accurately compute the instantaneous power output from the BIPV system is needed for prediction prior to decision-making. The detail algorithm of load shifting with support from BIPV dynamic model can be found in [5].

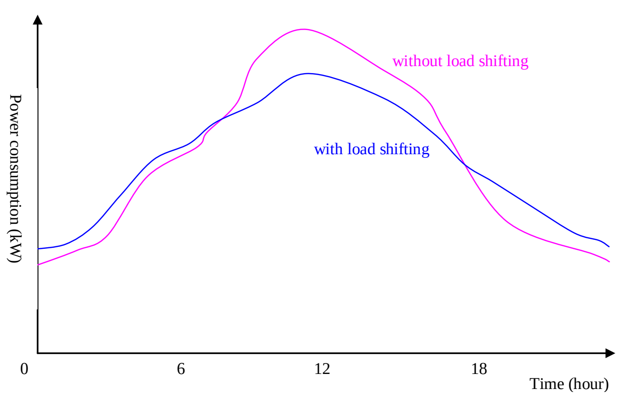

Fig. 3. Example of load profiles with and without load shifting control strategy.

III. VALUE OF DYNAMIC MODELS OF BIPV

In performing the function of load-shifting, one of the major pre-requisites is the ability of the BMS to predict the shape of the load profile in the day, so that re-scheduling of loads would then be possible. When the BMS has better knowledge on both the load profile (the demand) and the grid in co-generation with the BIPV system (the supply), its ability in deciding on the load shifting strategy would be more accurate. Besides load shifting, the BMS could also issue commands for energy management to attain maximum energy efficiency when the resulting load profiles is recorded more precisely. The resulting load profile is defined as the total power requirement of the whole building obtained by subtracting the contribution of the BIPV system from the actual load without any BMS control strategy.

For most types of building applications, with the exception of residential buildings, the uncontrolled load profiles are well matched with the BIPV generation profiles such that the BIPV power source is already acting as the peak clipping device. The application of BMS control strategy in load shifting must therefore take into consideration the supply from BIPV system when that component could be a significant source of power. Secondly, due to the thermal mass of the building, there exists certain time delay in the response of the power requirement of the HVAC system in the building from the solar radiation data. The BIPV system, on the contrary, is responding almost instantaneously to the solar irradiance. The dynamic model could therefore be applied in aiding the prediction of the load profile, besides considering its contribution to the overall consumption. Thirdly, the BIPV system could also contribute to reduce the cooling load of a building. These three contributions should therefore be considered thoroughly in the BMS control strategy to maximise the benefits of the installed BIPV. The research [5] has quantified these three aspects of the dynamic model developed as a demonstration of its application.

In formulating the control strategy of the BMS, the particular type of load under consideration is the controllable load. There are three main categories of power consumers that are controllable, namely: HVAC, lighting and lift. In the buildings in Hong Kong, HVAC is the single largest power user [6]. Hence HVAC has greatest potential for energy efficiency with BMS control. The research in [5] has therefore focused on the BMS control strategy applied to load shifting of HVAC systems, and assumed the BIPV contribution would have no effect on the control scheme of lighting and lift operations.

IV. PRINCIPLES OF APPLYING ARTIFICIAL INTELLIGENCE

With the advancement in BMS technology, more refined commands can now be issued to control the dynamic behaviour of different building components and systems. When applied in control of HVAC systems, the adjustment of air flow rate, chilled water temperature and flow rate, etc are all fine tuned instead of the traditional on/off control by a thermostat [7]. This could only be achieved by adopting more accurate sensors and sophisticated control algorithm done by computer programmes. The essence of control algorithm is inherent in the ability of the software to mimic human intelligence in decision-making. One of the new developments in computing is the development of Artificial

Intelligence (AI).

AI is a collection of methodologies devised for computer programming. It comprises at least 4 major categories: Fuzzy Logic Control (FLC), Artificial Neural Network (ANN), Genetic Algorithm (GA), and Case-based Reasoning (CBR) in BMS applications. The other AI methods developed (for instance the expert systems) are less common in BMS, and are therefore not discussed in this paper.

Fuzzy Logic Control (FLC) rooted from the fuzzy set theory proposed by Zadeh [8] back in 1965. Its approach is to imitate our daily approximate reasoning in decision making. To do so, the input parameters (in numerical format) have to be changed to linguistic variables (fuzzy sets). This is particular useful when human perception (like thermal comfort) is concerned where the nature of data is best represented in a fuzzy manner. Therefore FLC has a long history of application in control of HVAC systems [9]. Detail construction of the BMS control strategy utilising AI shall refer to [5].

Artificial Neural Network (ANN) is based on the human knowledge about biological neural network, which is a flow of signal (information) through nodes of neurons. In the ANN, an artificial neuron receives inputs from other neurons, and then passes onto the next layer of neuron by adjusting the level of strength of the signal. When the signal passes through a few layers of neurons, the input signals are modified in such a way to give out the proper response which is learnt through experience. By simulating a multiple connections between layers of neurons, an ANN is capable of analysing large amount of data to establish the relationship between past, current and future parameters. As a result, it is frequently used in prediction, for examples the electricity load profile predictions implemented by utilities [10]. ANN can therefore be adopted for training of the Fuzzy Logic Control. This is done by acquiring input from the dynamic BIPV model developed.

V. Dynamic BIPV modelling techniques

Photovoltaic (PV) modules can serve as the building envelope to keep out the weather and control heat gain together with its primary function of generating electricity on-site. To analysis the electrical performance of a PV module, both the instantaneous power output and the energy yield over the time period under investigation should be considered. Instantaneous power has been normalised to per unit power under Standard Test Conditions (STC) for easy comparison between different types of technology. STC is the PV industry convention for benchmarking the conversion efficiencies of a PV cell under a set of particular testing circumstances. It is defined as the tests being conducted when the PV cell is operating at 25^{o}C, receiving a 1000W/m^2 solar irradiance, at which the spectrum of light rays shall be as though it passes through a relative air mass of 1.5. Relative air mass is the measurement of relative path of sunlight passing through the atmosphere before reaching the PV panels, and is defined to be 1.0 when the sun is directly overhead. Although STC is widely accepted as the industry standard, there are certain researchers asserted that these measuring conditions do not correspond to the real operating conditions [11]. Hence a dynamic model to characterise the performance of a PV system in a detail manner will support the designers to assess the performance of a BIPV system, and also serve as an input to the BMS for more accurate control algorithm.

Many of the PV system simulation programmes are based on time-series analysis making use of hourly environmental data which is more readily available. Gansler et al. [12] asserted that hourly data are only suitable for systems responding slowly or linearly to changes in solar radiation. This is certainly not the case for PV systems which are responding almost instantaneously to changes in solar irradiance. Also, Durisch et al. [11] successfully showed that the change in PV conversion efficiency with respect to solar irradiance is non-linear. Gansler et al. demonstrated that the error in estimation of PV energy yield by using hourly solar radiation data as compared with that of 1-minute data could be as high as 35% [12]. Following on his work, Vijayakumar et al. [13] reported the study on the possible errors resulted from using averaged hourly solar radiation data instead of 1-minute or 3-minute data to be in the range of 5 - 50%. Neither of their work, however, included the detail study on the temperature coefficient of the PV modules, which is also an important factor affecting its performance. The error in estimation of PV energy yield is expected to be much larger in those partly cloudy days when the solar irradiance is changing rapidly. To illustrate the effect of using 1-hour data instead of data at a more frequent interval, a chart showing both cases are shown below in Fig. 5. The main contribution of the research [5] is therefore to make use of short-term environmental data input for calculation of instantaneous power output of a BIPV system to account for the dynamic properties of a BIPV system. Subsequently, this dynamic model could be used as an input for the BMS control strategy.

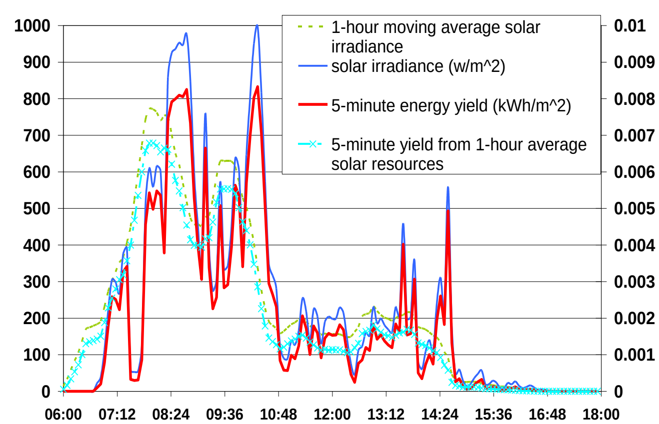

Fig. 4. Comparison of 5-minute to 1-hour data for a PV system

VI. Incorporating BIPV input for BMS control

At the building system level, the BMS will have to measure and predict the electricity contribution from BIPV system; and then issue proper commands to the HVAC plants for load shifting. The parameters resolved for individual BIPV system can be applied for gathering information about the environmental and thermal characteristics of the building envelope. Since the dynamic model devised is reflecting the immediate properties of the building envelope, it is providing valuable information to the BMS control. This valuable information can be utilised in the following ways:

i. to be taken as one of the linguistic inputs for the FLC in adjusting the HVAC set points when real-time BIPV output is measured;

ii. the dynamic model estimates the contribution from the BIPV systems to the total building loads;

iii. to be stored for off-line training of the proposed Neural-Fuzzy Controller.

To better utilise the expert knowledge gained from monitoring of the PV system as a building envelope, the hybrid approach would take FLC as the core structure. Therefore a Neural-Fuzzy Controller is proposed for taking the second part of the valuable information listed above. The proposed structure of BMS control of HVAC plants for thermal comfort control and peak load clipping taking BIPV dynamic model input to be as follows:

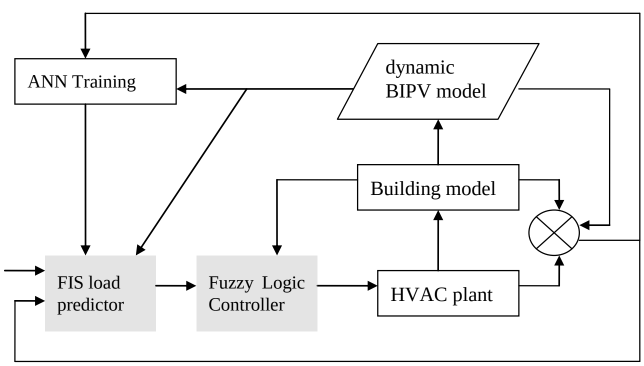

Fig. 5. Proposed structure of Neural-Fuzzy Controller incorporating dynamic modelling of BIPV system.

VII. CONCLUSIONS

Different PV technologies demonstrate different behaviour under different environmental conditions. The intermittent and highly versatile nature of BIPV system necessitates a modelling technique that can estimate its performance at high accuracy and short time intervals. The core part of the dynamic model is an empirical model with parameters to be determined experimentally. A dynamic model to characterise the performance of a BIPV system in a detail manner can support the designers to assess the performance of such system, and also serve as an input to the BMS for more accurate control algorithm. The research by Gansler et al. [12] and Vijayakumar et al. [13] demonstrated the error in estimation of PV energy yield by using hourly solar radiation data as compared with that of 1-minute data could be as high as 35%.

The application of BMS control strategy in load shifting has to take into consideration of the supply from BIPV system when that component could be a significant source of power. The BIPV system is responding almost instantaneously to the solar irradiance while that of HVAC load has a certain time delay due to building thermal mass. The dynamic BIPV model could therefore be applied in aiding the prediction of the load profile, besides considering its contribution to the overall consumption. Thirdly, the BIPV system could also contribute to reduce the cooling load of a building [14]. These three contributions should therefore be considered thoroughly in the BMS control strategy to maximise the benefits of the installed BIPV.

VIII. REFERENCES

[1] J. G. Wang, and T. H. Shun, *Renewable Energy Applications and Building Energy Efficiency*, Beijing: China Machine Press, 2004, p. 271. (in Chinese).

[2] K. J. Moss, *Energy Management in Buildings*, London: Taylor & Francis Group, 2006, p. 2

[3] S. Kumar, S. Sinha, T. Kojima, and H. Yoshida, "Development of parameter based fault detection and diagnosis technique for energy efficient building management system", *Energy Conversion and Management*, Vol. 42, pp. 833-854, 2001.

[4] Z. J. Paracha, and P. Doulai, "Load Management Techniques and Methods in Electric Power System", in *Proc. 1998 International Conference on Energy Management and Power Delivery*, pp. 215-216.

[5] K. H. Lam, "Techniques for Dynamic Modelling of BIPV in Supporting System Design and BEMS," Ph.D. dissertation, Dept. Architecture, The University of Hong Kong, Hong Kong, 2007. Available: http://sunzi1.lib.hku.hk/hkuto/record/B39558460

[6] Electrical and Mechanical Services Department (EMSD) HKSAR, *Hong Kong Energy End-use Data*, September 2005, Hong Kong.

[7] G. J. Levermore, *Building Energy Management Systems: Application to low-energy HVAC and natural ventilation control*, London: E & FN Spon, 2000, pp. 141-145.

[8] L. R. Medsker, *Hybrid Intelligent Systems*, Boston: Kluwer Academic Publishers, 1995, p. 7.

[9] M. Jamshidi, "On Fuzzy Control of Nonchlorofluorocarbon Air-Conditioning Systems" in J. Yen et al. (eds.), *Industrial applications of fuzzy logic and intelligent systems*, pp. 247-276,

[10] D. C. Park et al., "Electric Load Forecasting Using an Artificial Nueral Network", in *Proc. 1991 IEEE Transaction on Power Systems*, Vol. 6, No. 2, pp. 442-449.

[11] W. Durisch, K. H. Lam, and J. Close, "Behaviour of a Copper Indium Gallium Diselenide Module under real Operating Conditions", in *Proc. World Renewable Energy Congress VII*, July 2002, Cologne, Germany.

[12] R. A. Gansler, S. A. Klein, and W. A. Beckman, "Investigation of Minute Solar Radiation Data", *Solar Energy*, Vol. 55, No. 1, pp. 21-27, 1995.

[13] G. Vijayakumar, M. Kummert, S. A. Klein, and W. A. Beckman, "Analysis of short-term Solar Radiation Data", *Solar Energy*, Vol. 79, pp. 495-504, 2005.

[14] A. H. Fanney, E. R. Weise, and K. R. Henderson, "Measured Impact of a Rooftop Photovoltaic System", *Journal of Solar Energy Engineering*, Vol. 125, pp.245-250., 2003