Proceedings of 2012 International Conference on
Modelling, Identification and Control, Wuhan, China, June 24-26, 2012

Power Decomposition Based on SVM Regression

Jiaming Li[1], Sam West[2], Glenn Platt[2]
[1]CSIRO ICT Centre, Australia, [2] CSIRO Energy Technology, Australia

***Abstract*—For more efficient energy consumption, it is crucial to have accurate information on how power is being consumed through a single power measurement. It benefits both market participants such as retailers, network businesses and also power consumers. This means that the metering device must not only be able to distinguish between different loads on a common circuit, but also decipher their respective power consumption. This paper gives our investigation on power load signature and power decomposition. In particular, the paper focuses on the development of power decomposition algorithm based on support vector machine (SVM) regression, i.e, estimating the power proportion of constant power (CP) loads to constant impedance (CI) loads. The power decomposition algorithm in this paper works on steady-state power load signal.**

***Index Terms*— Power Decomposition; SVM Regression; Power Load Classification; Power Load Signature**

I. Introduction

THE electricity industry in many countries is facing a number of new pressures due to increasing demand and the prospect of carbon accountability. Demand management and reducing carbon emissions both encourage energy efficiency. The research on energy efficiency is becoming a significant topic in power system resource planning and operations.

There are two popular ways to improve energy efficiency. One is through demand management and optimization [1-6]. Another is to strengthen the link between utility companies and their customers by providing a better understanding of the usage and consumption of electric power. The second way gives households the ability to manage their own energy use by providing consumers accurate information about how power is being consumed, i.e., how much energy each power load is using and the costs at any time. Deeper consumer engagement is important. The consumers can set their power load to run on off-peak power. The detailed power load information also benefits to market participants such as utilities, customers, regulators, appliance manufacturers and other stakeholders. A utility can improve planning and operations and develop new products and services, such as enhanced building audits and operation and other energy services. Customers benefit from reduced costs and improvements in power quality and reliability. Regulators can produce better policies and rules. Manufacturers of appliances and equipment can improve quality and compliance, while anticipating market demands and providing more effective and efficient products. Everyone benefits from the increased overall efficiencies.

Traditionally, the second way requires individual metering (sensor) of each power load of interest. It is inherently inconvenient and costly. Currently, one household usually has a single power meter. It measures the total action of all the electricity devices within a household. To provide much more useful information to the resident, allowing them to understand their consumption in much greater detail, and improving the energy efficiency, a solution is to decompose the power demand from such single power meter to identify which loads are active by using power load classification and decomposition technique, which is the opposite way of data fusion technologies [7, 8] that can combine information from heterogeneous sensors to obtain synergistic observation effects. This solution allows just one meter to be connected to the incoming electrical supply of a residence. It is obviously easier, cheaper and certainly more convenient.

This solution means that the metering device must not only be able to distinguish between different loads on a common circuit, but also decipher their respective power consumption. A novel methodology called power signature analysis or non-intrusive load metering (NILM) [9 – 14] have been developed and become a hot research topic. It is used to decomposition the power demands of different electricity devices from single smart meter measurement to identify the load mixture, i.e. what types of loads are active and how much power they are consuming.

This paper gives our investigation on power load representation and power decomposition using unique power signature of each load. In particular, the paper focuses on the development of power decomposition algorithm based on support vector machine (SVM) regression, i.e, estimating the power proportion of constant power (CP) loads to constant impedance (CI) loads.

This paper is organized as follows. Section II gives brief introduction about SVM. Section III introduces our investigation about how to better represent the power load and presents our power decomposition algorithm based on SVM regression. Section IV gives some experimental results to quantify the performance. Finally, a conclusion is drawn in Section V.

II. Support Vector Machine

Support vector machines (SVMs) are a set of supervised learning methods that analyze data and recognize pattern, used for classification. As a powerful classification algorithm, SVMs [15] generate the maximal margin hyperplane in a feature space defined by a kernel function. For the binary classification problem, the goal of an SVM is to find an optimal hyperplane $f(x)$ to separate the positive examples from the negative ones. The points which lie on the hyperplane satisfy

$$\langle w, x\rangle + b = 0 .$$

The decision function which gives the maximum margin is

$$f(x) = sign(\sum_{i=1}^{m} y_i \alpha_i \langle x, x_i\rangle + b). \tag{1}$$

The parameter α_i is non-zero only for inputs x_i closest to the hyperplane $f(x)$ (within the functional margin). All the other parameters α_i are zero. The inputs with non-zero α_i are called *support vectors*.

Notice $f(x)$ depends only on the inner products between inputs. Suppose the data are mapped to some other inner product space *S* via a nonlinear map

$$\Phi : \Re^d \to S .$$

Now the above linear algorithm will operate in *S*, which would only depend on the data through inner products in

$$S : \langle \Phi(x_i), \Phi(x_j)\rangle .$$

Boser, Guyon and Vapnik [15] showed that there is a simple function k such that

$$k(x, x_i) = \langle \Phi(x), \Phi(x_i)\rangle ,$$

which can be evaluated efficiently. The function *k* is called a *kernel*. So we only need to use the kernel *k* in the optimization algorithm and never need to explicitly know what Φ is.

For linear SVM, the kernel k is just the inner product in the input space, i.e.

$$k(x, x_i) = \langle x, x_i\rangle ,$$

and the corresponding decision function is (1).

For nonlinear SVM, there are a number of kernel functions which have been found to provide good performance, such as polynomials and radial basis function (RBF). Here we explore the polynomials and RBF kernel functions as follows:

- RBF kernel: $k(x, x_i) = \exp(-\frac{\| x - x_i \|^2}{2\sigma^2})$,
- Polynomial kernel: $k(x, x_i) = (\langle x, x_i\rangle + b)^d$.

The corresponding decision function for a nonlinear SVM is

$$f(x) = sign(\sum_{i=1}^{m} y_i \alpha_i k(x, x_i) + b).$$

III. Investigation of Power Load Representation and Power Decomposition

This section, we will present our investigation on the representation of power loads, give different ways to represent the power loads and clarify which presentation is better for power load classification and decomposition. This section also gives our power decomposition algorithm based on SVM regression.

A. Database

The database recorded switching or running data for ten common household appliances as blow. Each data consists of high speed samples (50 kHz) of voltage and current from each phase.

1. Electric jug
2. Toaster
3. Lamp
4. Heater
5. Florescent light
6. PC with LCD monitor
7. PC
8. LCD monitor
9. Laptop
10. Air conditioner

Different state data is recorded for some of the appliances, such as running, switching on, switching off, etc. So the database contains total 33 data for ten household appliances. Our initial investigations are carried out based on it.

Database:

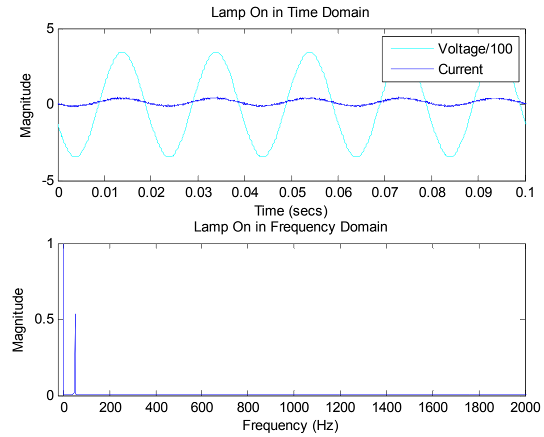
1 FullLoadHeaterTest_clip
2 fanloadheatertest
3 fanloadheatertest_clip
4 fluro_noload
5 fluro_on
6 fluro_switching
7 fullloadheatertest
8 halfloadheatload
9 halfloadheatload_clip
10 heater_switching_on
11 jug_noload
12 jug_on
13 jug_switchingoff
14 jug_switchingon
15 lamp_noload
16 lamp_switching
17 lampon
18 laptop_running
19 laptop_startingup
20 laptop_supplyconnected
21 laptop_supplyonly
22 lcd_running
23 noloadheatertest
24 noloadheatertest_clip
25 pc_lcd_monitorstandby
26 pc_lcd_noload
27 pc_lcd_running
28 pc_lcd_starting
29 pc_running
30 test2
31 toaster_noload
32 toaster_on
33 toaster_switching

B. Load Representation and Power Decomposition

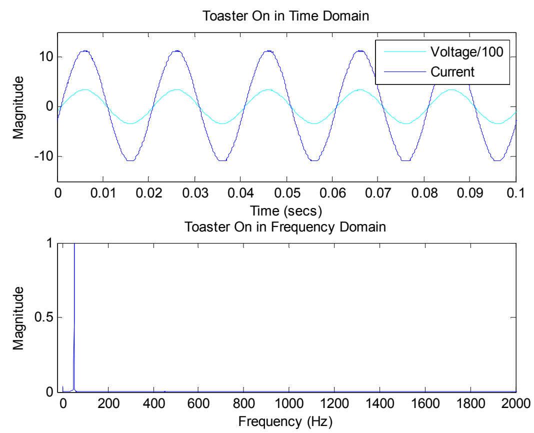
We developed power decomposition algorithm based on SVM regression methodology using the distinction of load current representation in frequency domain. The following subsection will give detailed introduction about the algorithm.

1) Power Load Representation

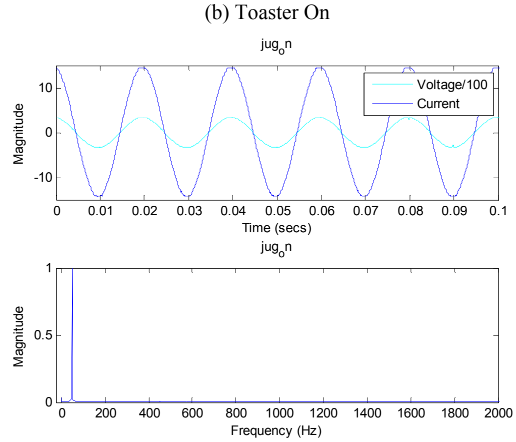
Figure 1 and 2 present us current representation of some power loads in time and frequency domain. We can see that for different power loads, the current representation in frequency domain are different, especially for different types of load, such as between resistive loads and switching loads. Frequency representations of resistive loads concentrate on lower frequency components comparing to switching loads, which spread their frequency representation in both low and high frequency components.



(a) lamp On

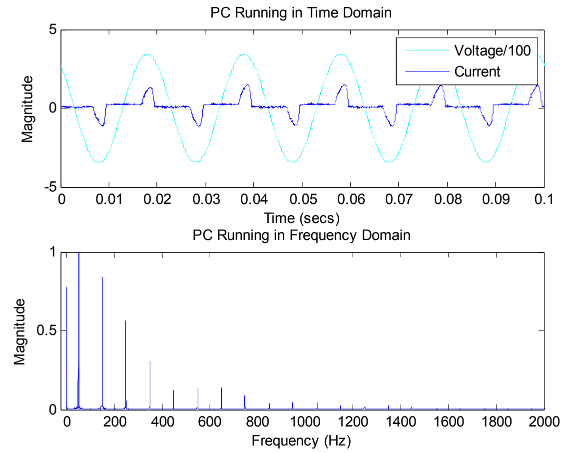


(b) Toaster On

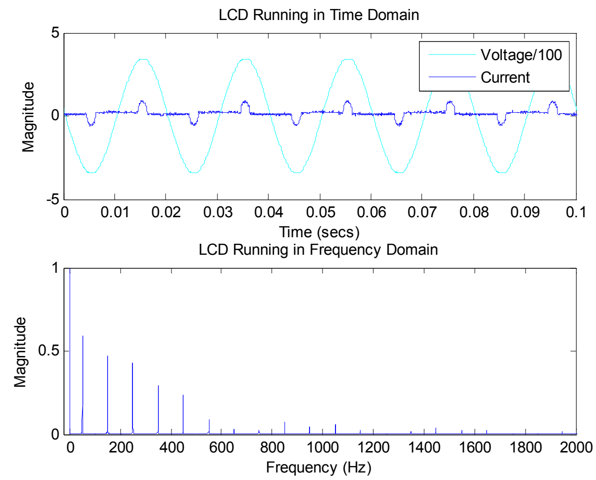


(c) Jug On

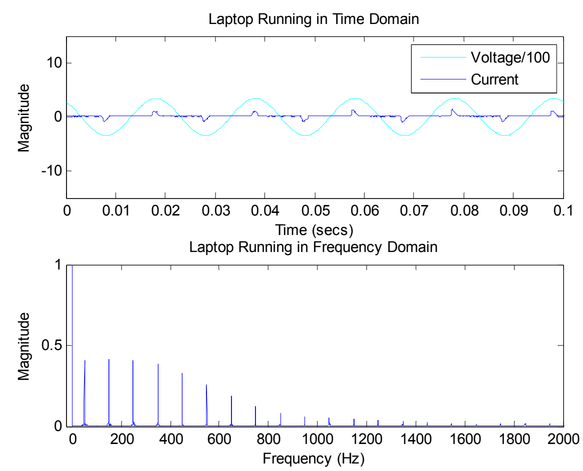
Fig 1: Current Representation of Resistive Loads in Time and Frequency Domain



(a) PC Running



(b) LCD Running



(c) LapTop Running

Fig 2: Current Representation of Switching Loads in Time and Frequency Domain

2) Power Decomposition Algorithm

Figure 1 & 2 has shown us the distinction among load current representation in frequency domain, especially between resistive loads and switching loads. Most of constant impedance loads are resistive loads and constant power loads are switching loads. Using this characteristic, the algorithm to estimate the power proportion of constant power (CP) loads to constant impedance (CI) loads has been developed.

Figure 3 is the flow chat of our SVM regression based CP/CI power decomposition system. Firstly, the second phase load current is normalized and transformed to frequency domain. Since the first numbers of frequency components or harmonics contain most information of the load, the first numbers of components are selected as input for SVM regression based CP/CI Power Proportion model, which gives real value of CP/CI power proportion.

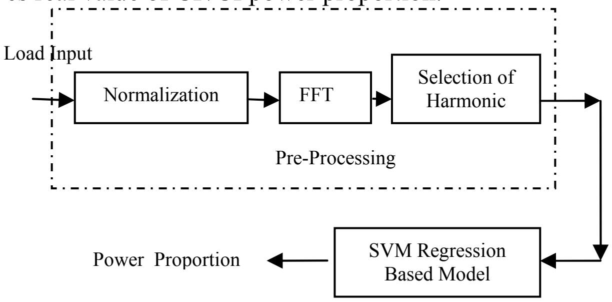


Fig 3: Diagram of SVM Regression Based Power Decomposition

For power decomposition, part of the data introduced in section III-A is used for training, the rest for testing.

As shown in Figure 3, our algorithm uses the distinction frequency representation of load current. An SVM is applied to learn the pattern.

IV. Experimental Results

Six loads, pc_running, lcd_running, pcLcd_running jug_on, toaster_on and lamp_on, are selected for training and testing. The first 300 numbers of FFT components are selected. Tests are performed for different group of test loads. 100 times of repeat tests performed for each group. In each test the random combination loads (random CP/CI ratio) are selected. To guarantee enough and evenly distributed training data, the ratio 0-100% is divided by 10 equal interval, i.e. 0-10%, 1-20%, …, 90-100%. The same numbers of training data is selected for each interval. Figure 4 presents the test performance for difference size of training data in each interval. From the figure, we can see that the more data for training, the more accuracy prediction we can generate. Since the PC memory limitation, 160 numbers of training data for each interval is the maximum one we can use.

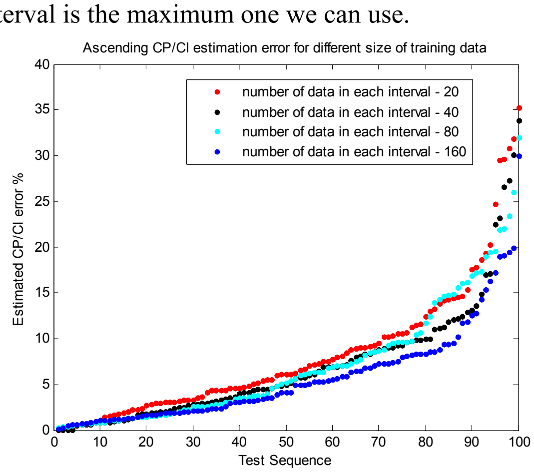
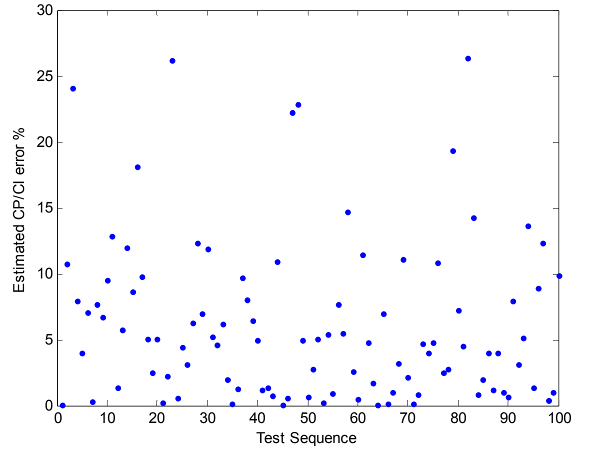
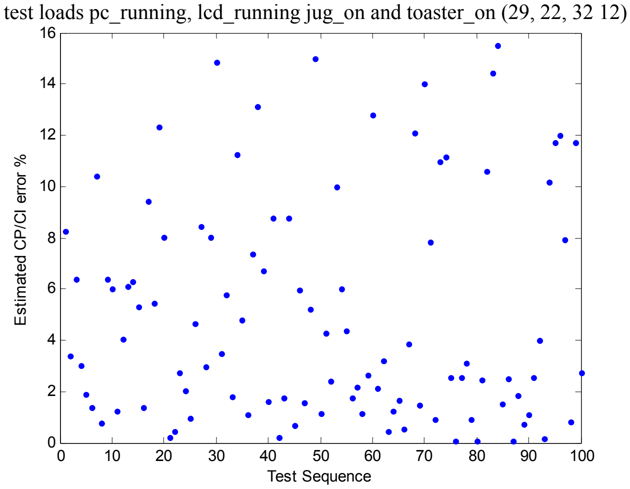


Fig 4: Performance comparison for different size of training data

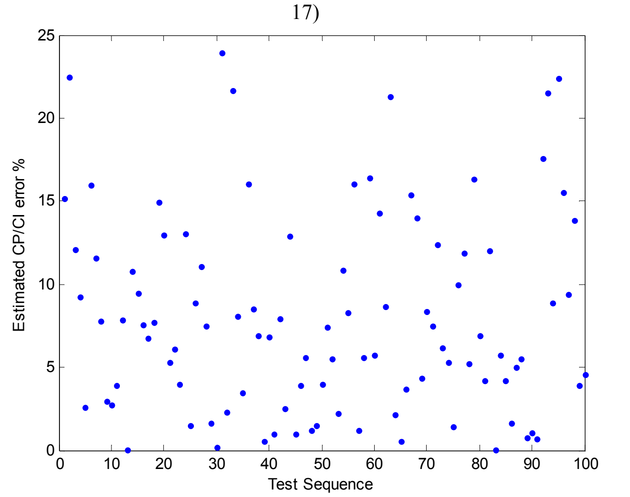
Figure 5 presents SVM regression based CP/CI power decomposition results using 160 training data in each interval. From figure 5, we can see that 99% real CP/CI estimation error is less than 25%.



(a) test loads pc_running, lcd_running jug_on and toaster_on (29, 22, 32 12)



(b) test loads pc_running, pcLcd_running, jug_on and lamp_on (29, 27, 32 17)



(c) test loads lcd_running, pcLcd_running, toaster_on and lamp_on (22, 27, 12 17)

Fig 5: Real CP/CI estimation Error

In order to see estimation performance, estimation errors are quantized in 11 intervals, i.e., 0, 10, 20, …, 100. Table 1 gives the number of tests with certain CP/CI estimation error for different group of loads. Table 4 gives the number of tests with cumulative CP/CI estimation error. In table 1 & 2, loads pc_running, lcd_running, pcLcd_running jug_on, toaster_on and lamp_on are labelled as 29, 22, 27, 12, 32, 17 respectively. From these tables we can see that almost 99.7% numbers of estimation error is less than 20%. 88% numbers of estimation error is less than 10%, 45% numbers can achieve accurate CP/CI estimation.

Table 1: The number of tests with certain CP/CI estimation error

CP/CI Estimation Error%	0	10	20	30	40	50	60	70
Test loads (27,22,12,17)	41	53	6	0	0	0	0	0
Test loads (29,22,12,32)	52	38	9	1	0	0	0	0
Test loads (27,29,32,17)	43	47	10	0	0	0	0	0

Table 2: The cumulative number of tests with certain CP/CI classification error

CP/CI Estimation Error%	0	10	20
Test loads(27, 22, 12, 17)	41	84	100
Test loads(29, 22, 12, 32)	52	90	99
Test loads(27, 29, 32, 17)	43	90	100
Total	136 (45%)	264 (88%)	299 (99.7%)

V. CONCLUSIONS

Our preliminary investigation has shown us that algorithm based on SVM regression methodology works well for power decomposition. Further work can be done based on such preliminary study. For example, the higher accuracy in decomposition may be achieved by combining the steady-state and transient approaches; not only using frequency representation but also using time representation for classification and decomposition; using data fusion and different machine learning technologies such as genetic algorithm, which has been successfully applied to problems in a variety of multi-sensor systems, range from optimization [1-2], localization [16, 17], self-organization [18], photovoltaic aggregation [19], multi-agent coordination [3-7], modelling [20, 21] and control [22, 23].

VI. REFERENCES

[1] Y. Guo, et al., "Evolutionary Optimisation of Distributed Energy Resources" Proceedings, 18th Australian Joint Conference on Artificial Intelligence – AI 2005: Advances in Artificial Intelligence, **Syd**ney, Australia, Dec 2005, vol. 3809, pp. 1086-1091.

[2] R. Li, et al.,, "Agent-Based Optimisation Systems for Electrical Load Management" Proc. First International Workshop on Optimisation in Multi-Agent Systems, Estoril, Portugal, May 2008, pp 60-69.

[3] J. Li, et al., "Performance of Multi-agent Coordination of Distributed Energy Resources" WSEAS Transactions on System and Control, January 2007, Issue 1, Vol. 2, pp 52-58.

[4] J. Li, et al., "Agent-Based Distributed Energy Management" 20th Australian Joint Conference on Artificial Intelligence- AI 2007: Advances in Artificial Intelligence, Dec. 2007, Australia, Volume: 4830, pp569-578.

[5] S. Luo, et al.,, 'A smart fridge with an ability to enhance health and enable better nutrition' International Journal of Multimedia and Ubiquitous Engineering, Vol. 4, No. 2, pp. 66-80, April, 2009.

[6] J. Li, et al., "Coordination of Distributed Energy Resource Agents", Journal of Applied Artificial Intelligence, Volume 24, Issue 5, May 2010, pages 351 – 380.

[7] N. Xiong, P. Svensson, "Multi-sensor management for information fusion: issues and approaches", Information Fusion 3 (2002), pp.163–186

[8] J. Li, et al., "Sensor Data Fusion for Accurate Cloud Presence Prediction Using Dempster-Shafer Evidence Theory", Sensors 2010, 10(10), 9384-9396.

[9] S. Drenker and A. Kader, "Nonintrusive monitoring of electrical loads," *IEEE Comput. Appl. Power*, vol. 12, no. 4, pp. 47-51, 1999.

[10] C. Laughman, et al., "Power Signature Analysis", IEEE Power & Energy Magazine, March/April 2003.

[11] M.L. Marceau, R. Zmeureanu, "Nonintrusive load disaggregation computer program to estimate the energy consumption of major end uses in residential buildings", Energy Conversion & Management 41 (2000), 1389-1403.

[12] Hart, G.W.: Non-intrusive Appliance Load Monitoring. In: Proc. 1992 IEEE Conference, vol. 80, pp. 1870–1891 (1992).

[13] Hsueh-Hsien Chang, et al., "Load Identification in Neural Networks for a Non-intrusive Monitoring of Industrial Electrical Loads", Computer Supported Cooperative Work in Design IV: 11th International Conference, CSCWD 2007, Melbourne, Australia, April 26-28, 2007, Pages: 664 – 674.

[14] W.L. Chan, et al., "Harmonics Load Signature Recognition by Wavelet Transforms", International Conference on Electric Utility Deregulation and Restructuring and Power Technologies, City University, London, 4-7 April 2000, pp 666-671.

[15] V. Vapnik. "The Nature of Statistical Learning Theory". Springer, N.Y.,1995.

[16] M. Romoozi, H. Ebrahimpour-komleh, "A Positioning Method in Wireless Sensor Networks Using Genetic Algorithms ", JDCTA, AICIT, Vol. 4, No. 9, pp. 174-179, 2010.

[17] J. Li, et al., "Critical Damage Reporting in Intelligent Sensor Networks" Proceedings, 17th Australian Joint Conference on Artificial Intelligence – AI04: Advances in Artificial Intelligence, 6th - 10th December 2004, Cairns, Australia, vol. 3339, pp. 26-38.

[18] G. Poulton, et al. "Directed self-assembly of 2-dimensional Meso-blocks using Top-down/Bottom-up design", Engineering Self-Organising Systems: Methodologies and Applications, May 2005, Vol. 3464, pp. 154-166.

[19] G. Platt, et al., "The Virtual Power Station" 2008 IEEE International Conference on Sustainable Energy Technologies (ICSET2008), Vols 1 and 2, Nov. 2008, pp. 526-530.

[20] G. Platt, et al., "Adaptive HVAC Zone Modeling for Sustainable Buildings", Journal of Energy and Buildings, Vol.42, Issue 4, April 2010, pp. 412–421.

[21] J. Li, et al., "Dynamic Zone Modelling for HVAC System Control" International Journal of Modelling and Identification and Control, Vol. 9, Nos. 1/2, 2010, pp. 5-14.

[22] J. Li, et al., "HVAC control strategies for thermal comfort and indoor air quality", International Journal of Advanced Mechatronic Systems (IJAMechS), Vol. 3, No.1, 2011, pp24-32.

[23] J. Li, et al., "Indoor Air Quality Control of HVAC System" International Conference on Modelling, Identification and Control, Okayama, Japan, July 17-19, 2010.