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► **To cite this version:**

Subodh Paudel, Mohamed Elmtiri, Wil Kling, Olivier Le Corre, Bruno Lacarrière. Pseudo Dynamic Transitional Modeling of Building Heating Energy Demand Using Artificial Neural Network. *Energy and Buildings*, 2014, 70C, pp. 81-93, S0378-7788(13)00758-5. 10.1016/j.enbuild.2013.11.051 . hal-00916275

**HAL Id: hal-00916275**

**<https://hal.science/hal-00916275>**

Submitted on 12 Dec 2013

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1 **Pseudo Dynamic Transitional Modeling of Building Heating Energy Demand Using Artificial**  
2 **Neural Network**

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10 **Abstract**

11 This paper presents the building heating demand prediction model with occupancy profile and  
12 operational heating power level characteristics in short time horizon (a couple of days) using artificial  
13 neural network. In addition, novel pseudo dynamic transitional model is introduced, which consider  
14 time dependent attributes of operational power level characteristics and its effect in the overall model  
15 performance is outlined. Pseudo dynamic model is applied to a case study of French Institution  
16 building and compared its results with static and other pseudo dynamic neural network models. The  
17 results show the coefficients of correlation in static and pseudo dynamic neural network model of 0.82  
18 and 0.89 (with energy consumption error of 0.02%) during the learning phase, and 0.61 and 0.85  
19 during the prediction phase respectively. Further, orthogonal array design is applied to the pseudo  
20 dynamic model to check the schedule of occupancy profile and operational heating power level  
21 characteristics. The results show the new schedule and provide the robust design for pseudo dynamic  
22 model. Due to prediction in short time horizon, it finds application for Energy Services Company  
23 (ESCOs) to manage the heating load for dynamic control of heat production system.

24 **Keywords:** Building Energy Prediction; Short term building energy forecasting; Operational Heating  
25 Characteristics; Occupancy Profile; Artificial Neural Network; Orthogonal Arrays

## 29 1. Introduction

1  
2  
3 30 The global concerns of climate change and regulation in energy emissions have drawn more  
4  
5 31 attention towards researchers and industries for the design and implementation of energy systems for  
6  
7 32 low energy buildings. According to IEA statistics [1], total energy use globally accounts for around  
8  
9 33 7200 Mtoe (Mega Tonnes Oil Equivalent). Residential and commercial buildings consume 40% of  
10  
11 34 final energy use in the world and European countries consume 76% of energy towards thermal comfort  
12  
13 35 in buildings. The small deviations in design parameters of buildings could bring large adverse effect in  
14  
15 36 the energy efficiency and which, additionally, results in huge emissions from the buildings. It is  
16  
17 37 estimated that improvement in energy efficiency of the buildings in European Union by 20% will result  
18  
19 38 in saving at least 60 billion Euro annually [2]. So, research is very active in driving towards the  
20  
21 39 sustainable/low energy buildings. In order to accomplish this and to ensure thermal comfort, it is  
22  
23 40 essential to know energy flows and energy demand of the buildings for the control of heating and  
24  
25 41 cooling energy production from plant systems. The energy demand of the building system, thus,  
26  
27 42 depends on physical and geometrical parameters of buildings, operational characteristics of heating  
28  
29 43 and cooling energy plant systems, weather conditions, appliances characteristics and internal gains.

30  
31 44 There are various approaches to predict building energy demand based on physical methods  
32  
33 45 and data-driven methods (statistical and regression methods and artificial intelligence methods) as  
34  
35 46 mentioned by Zhao et al. [3]. Physical methods are based on physical engineering methods and uses  
36  
37 47 thermodynamics and heat transfer characteristics to determine the energy demand of the building.  
38  
39 48 There are numerous physical simulation tools developed as EnergyPlus [4], ESP-r [5], IBPT [6],  
40  
41 49 SIMBAD [7], TRNSYS [8], CARNOT [9] etc... to compute the building energy demand. A simplified  
42  
43 50 physical model based on physical, geometrical, climatic and occupant model was presented by  
44  
45 51 Duanmu et al. [10] to bridge the complexities of collecting more physical data required in simulation  
46  
47 52 tools. Other possible approaches for building energy prediction are semi-physical models like  
48  
49 53 response factor method, transfer function method, frequency analysis method and lumped method  
50  
51 54 [11]. Though methodologies adapted to estimate energy demand of buildings are different in physical  
52  
53 55 and semi-physical models, both are highly parameterized. In addition, physical parameters of buildings  
54  
55 56 are not always known or even sometimes data are missing. And also, these models are  
56  
57 57 computationally expensive for Energy Services Company (ESCOs) to manage heating and cooling  
58  
59 58 loads for control applications.  
60  
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65

59 Other approaches to predict building energy demand with limited physical parameters are  
1  
2 60 data-driven methods, which strongly dependent on the measurements of historical data. Statistical and  
3  
4 61 regression methods seem more feasible to predict building energy demand with limited physical  
5  
6 62 parameters. The statistical approaches have been widely used by Girardin et al. [12] to determine the  
7  
8 63 best model parameters by fitting actual data. Different approaches (physical and behaviour  
9  
10 64 characteristics based on statistical data) were presented by Yao et al. [13] to bridge the gap between  
11  
12 65 semi-physical and statistical methods. In their work, statistical daily load profile was grounded on  
13  
14 66 energy consumption per capita and human behaviour factor, and semi-physical method was based on  
15  
16 67 thermal resistance capacitance network. Nevertheless, these statistical models used linear  
17  
18 68 characteristics of input and output variables to evaluate the building parameters and are not adapted  
19  
20 69 to non-linear energy demand behavior. Regression models [14-15] have also been used to predict the  
21  
22 70 energy demand, but, they are not accurate enough to represent short term horizon (couple of days)  
23  
24 71 with hourly (or couple of minutes) sampling time energy demand prediction. In order to find the best  
25  
26 72 fitting from the actual data, this kind of models requires significant effort and time.

27  
28  
29 73 In recent years, there is a growth in research work in the field of artificial intelligence (AI) like  
30  
31 74 artificial neural network [3, 16] and support vector machines [3, 17-18]. These methods are known for  
32  
33 75 solving the complex non-linear function of energy demand models with limited physical parameters.  
34  
35 76 Neural network method has shown better performances than physical, statistical and regression  
36  
37 77 methods. Authors [19-20] used static neural network to predict energy demand of the building and  
38  
39 78 compared results with physical models. For instance, Kalogirou et al. [19] used climate variables  
40  
41 79 (mean and maximum of solar radiation, wind speed, and other parameters as wall and roof type)  
42  
43 80 coupled with artificial neural network (ANN) to predict daily heating and cooling load of the buildings. In  
44  
45 81 their work, results obtained using ANN are similar to those given by the physical modelling tool  
46  
47 82 TRNSYS. Neto et al. [20] presented a comparison of neural network approach with physical simulation  
48  
49 83 tool EnergyPlus. In this work, authors used climate variables as external dry temperature, relative  
50  
51 84 humidity and solar radiation as input variables to predict daily consumption of the building. Results  
52  
53 85 showed that neural network is slightly more accurate than EnergyPlus when comparing with real data.  
54  
55 86 Static neural network model proposed by Shilin et al. [21] consider climate variables as dry bulb  
56  
57 87 temperature and information regarding schedule of holiday's to predict cooling power of residential  
58  
59 88 buildings. Dong et al. [17] used support vector machine (SVM) to predict the monthly building energy  
60  
61  
62  
63  
64  
65

89 consumption using dry bulb temperature, relative humidity and global solar radiation. Performance of  
1  
2 90 SVM and neural network model were compared and results show that SVM was better than neural  
3  
4 91 network in prediction.  
5

6 92 Various authors [22-26] performed hourly building energy prediction using ANN. Mihalakakou  
7  
8 93 et al. [22] performed hourly prediction of residential buildings with solar radiation and multiple delays of  
9  
10 94 air temperature predictions as input variables. Ekici et al. [23] used building parameters (window's  
11  
12 95 transmittivity, building's orientation, and insulation thickness) and Dombayci [24] used time series  
13  
14 96 information of hour, day and month, and energy consumption of the previous hour to predict the hourly  
15  
16 97 heating energy consumptions. Gonzalez et al. [25] used time series information hour and day, current  
17  
18 98 energy consumption and predicted values of temperature as input variables to predict hourly energy  
19  
20 99 consumption of building system. Popescu et al. [26] used climate variables as solar radiation, wind  
21  
22 100 speed, outside temperature of previous 24 hours, and other variables as mass flow rate of hot water of  
23  
24 101 previous 24 hours and hot water temperature exit from plant system to predict the space hourly heat  
25  
26 102 consumptions of buildings. Li et al. [18] used SVM to predict hourly cooling load of office building using  
27  
28 103 climate variables as solar radiation, humidity and outdoor temperature. In their work, SVM was  
29  
30 104 compared with static neural network and result showed SVM better than static neural network in terms  
31  
32 105 of model performance. Dynamic neural network method which includes time dependence was  
33  
34 106 presented by Kato et al. [27] to predict heating load of district heating and cooling system based on  
35  
36 107 maximum and minimum air temperature. Kalogirou et al. [28] used Jordan Elman recurrent dynamic  
37  
38 108 network to predict energy consumption of a passive solar building system based on seasonal  
39  
40 109 information, masonry thickness and thermal insulation.  
41  
42  
43

44 110 For many authors [29-31] occupancy profile has a significant impact on building energy  
45  
46 111 consumption. Sun et al. [29] mentioned that occupancy profile period has a significant impact on initial  
47  
48 112 temperature requirement in the building during morning. In their work, reference day (the targeted day  
49  
50 113 prediction which depends on previous day and beginning of following day based on occupancy and  
51  
52 114 non-occupancy profile period) was calculated based on occupancy profile period. In addition to this  
53  
54 115 value, correlated weather data and prediction errors of previous 2 hours were used as input variables  
55  
56 116 to predict hourly cooling load. Yun et al. [30] used ARX (autoregressive with exogeneous i.e., external,  
57  
58 117 inputs) time and temperature indexed model with occupancy profile to predict hourly heating and  
59  
60 118 cooling load of building system and compared this with results given by neural network. Results  
61  
62  
63  
64  
65

119 showed that occupancy profile has a significant contribution in determination of auto regressive terms  
120 during different intervals of time and further showed a variation of it in the building heating and cooling  
121 energy consumption. The proposed ARX model showed similar performance with neural network.  
122 Sensitivity analysis for heating, cooling, hot water, equipment and lighting energy consumption based  
123 on occupancy profile was performed by Azar et al. [31] for different sizes of office buildings. In their  
124 work, they found that heating energy consumption has the highest sensitivity compared to cooling, hot  
125 water, equipment and lighting energy consumption for small size buildings. Also, results showed that  
126 heating energy consumption is highly influenced by occupancy profile for medium and small buildings  
127 during the occupancy period. Moreover, few literatures focused on operational power level  
128 characteristics (schedule of heating and cooling energy to manage energy production from plant  
129 system). For example, Leung et al. [32] used climate variables and operational characteristics of  
130 electrical power demand (power information of lighting, air-conditioning and office equipment which  
131 implicitly depends on occupancy schedule of electrical power demand) to predict hourly and daily  
132 building cooling load using neural network.

133 In conclusion, it can be reiterated that physical and semi-physical models [4-11], though give  
134 precise prediction of building energy, they are highly parameterized and are computationally expensive  
135 to manage the energy for control applications for ESCOs. Data-driven methods which depend on  
136 measurement historical data are not effective during the early stage of building operation and  
137 construction since measurement data are not available at these stages. When building energy data  
138 are available, data-driven methods can be considered if measurement data are accurate and reliable  
139 as this kind of models can be sensitive on the quality of measured data. Sensitivity of the accuracy of  
140 data driven models, thus, depends on the measurement data. Data-driven models based on statistical  
141 and regression methods [12-15, 26] cannot precisely represent short time horizon (couple of days)  
142 with hourly (or couple of minutes) sampling time prediction, though they perform prediction of energy  
143 consumptions of buildings with limited physical parameters. They also require significant efforts and  
144 time to compute the best fitting of the actual data. Static neural network models [19-21] are used for  
145 daily prediction and [22-25] are used for hourly prediction of the buildings energy consumptions.  
146 Though dynamic neural network model [27-28] gives better precision in compared to static neural  
147 network, they do not consider occupancy profile and operational power level characteristics of the  
148 plant system and therefore not adapted for the ESCOs to manage energy production for control

149 applications. The important features like transition and time dependent attributes of operational power  
150 level characteristics of the plant system are still missing, though, authors [29-30] consider occupancy  
151 profile and author [32] considers operational characteristics of electrical power demand. The detailed  
152 variables and application of models developed in the literature reviews are summarized in Table 1.

153 None of these studies has evaluated the transition and time dependent effects of operational  
154 power level characteristics of heating plant system and has predicted building heating energy demand  
155 in short time horizon (a couple of days). This short term prediction is important to ESCOs for dynamic  
156 control of heat plant system. This paper bridges the gap between static and dynamic neural network  
157 methods with occupancy profile and operational power level characteristics of heating plant system. It  
158 introduces novel pseudo dynamic model, which incorporates time dependent attributes of operational  
159 power level characteristics. Their effects on neural network model performances are compared to  
160 static neural network for building heating demand. Orthogonal arrays are applied to the proposed  
161 pseudo dynamic model for robust design and confirmed the new schedule of occupancy profile and  
162 operational heating power level characteristics obtained from ESCOs. The proposed method allows  
163 short term horizon prediction (around 4 days with sampling interval of 15 minutes) to make decision  
164 (e.g. management of wood power plant) for the ESCOs. The next section describes methodology  
165 including scope of study, design of transitional and pseudo dynamic characteristics, neural network  
166 model and orthogonal arrays. Finally, a case study is presented and results and discussion are drawn  
167 to analyze the performance of different static and pseudo dynamic models along with robustness of  
168 proposed pseudo dynamic model for heating demand prediction of the building.

Table 1: Summary of variables and application models in the literature

## 2. Methodology

171 The development and implementation of models proposed in this work are based on collection of  
172 real building heating demand, operational heating power level characteristics, climate variables and  
173 approximated occupancy profile data (see Appendix A for selection of relevant input variables). An  
174 outline of the methodology presented in this paper is shown in figure (1). The input of this methodology  
175 is in form of time-series climate and building heating energy data. The other inputs data are occupancy  
176 profile and operational heating power level characteristics for working and off-days for 24 hours.  
177 Dynamics of building heating demand is also an input to the methodology which includes settling and

178 steady state time and is estimated from real building data. Based on operational heating power level  
179 and dynamics of building characteristics, transitional and pseudo dynamic models are designed.  
180 Finally, neural networks for static and pseudo dynamic models are designed to predict heating  
181 demand in short time horizon (couple of days). For the robustness of pseudo dynamic model,  
182 occupancy profile and operational power level characteristics are analyzed for different time intervals  
183 to confirm occupancy schedule profile and operation of plant system from the orthogonal arrays. The  
184 pseudo dynamic model after optimum orthogonal arrays design is used for final prediction of the  
185 building heating demand. Scope of this study, details of transitional and pseudo dynamic model,  
186 neural network model and orthogonal arrays are described in section 2.1 - 2.4.

187 Figure 1: Outline of the proposed methodology on heating demand prediction

## 188 2.1 Scope of Study

189 The scope of this paper is heating demand prediction in short time horizon for the large building. The  
190 overall objective is to make an energy services decisions (e.g. management of wood power plant) for  
191 ESCOs. The assumptions carried for this study are highlighted as:

- 192 1. Winter period is studied.
- 193 2. Existing building is considered and space heating demand of this building is fed up from a heat  
194 network to a central substation. Domestic hot water (DHW) is out of the scope.
- 195 3. The heating demand data was recorded in data acquisition system database and thermal  
196 comfort inside the building was performed in this database. Thus, the effects of ventilation and  
197 air-conditioning on heating are already included in this database.
- 198 4. Simple occupancy profile of building is anticipated approximately to assist the ESCOs to  
199 schedule their heat production system. In such a system, individual occupant's behavior or  
200 precise occupancy profile is not considered. Thus, the modeling constraints are closer to the  
201 operational condition of ESCOs to estimate the heat demand.
- 202 5. The wind speed and direction are not taken into consideration. This is due to the fact that  
203 present weather variables data are taken from data acquisition system but future weather  
204 variables values are coming from an atmospheric modeling system which mesh size can be  
205 15 km (as ARPEGE, see [33]), 10 km (as ALADIN, see [34]) or 2.5 km (as AROME, see [35]).  
206 In such a case, wind impact on heating demand prediction of a specific building located inside



232 Figure 3: Transitional and Pseudo dynamic characteristics (for a day)

1  
2  
3 233 The transitional characteristics explicate the power transition level of operational  
4  
5 234 characteristics, however, dynamic information of power level attributes is still lacking. It means that  
6  
7 235 power content in operational characteristics of figure (2) of point 1-1' is not equal to 2-2'; point 3-3' is  
8  
9 236 not equal to the 4-4'; 5-5' is not equal to 6-6'; 7-7' is not equal to 8-8' and 9-9' is not equal to 10-10'.  
10  
11 237 Dynamic transition information, thus, is necessary in the model which considers dynamic  
12  
13 238 characteristics of the building. The simple first order dynamics of building characteristic is shown in  
14  
15 239 figure (4), where  $\tau$  represents time constant.

16  
17  
18 240 Figure 4: Dynamics of building characteristics

19  
20  
21 241 In figure (4), delay represents time it takes from plant system to reach the building for heating  
22  
23 242 operation and after this, power is sufficient to provide heating demand. The  $\tau$  represents the 63% of  
24  
25 243 power transferred to the building heating system from plant system. Other dynamics to incorporate is  
26  
27 244 settling time ( $T_s$ ), which is the time elapsed for heating power to reach and remain within the specified  
28  
29 245 error band and equal to  $[2\tau, 5\tau]$  and have almost similar behavior like steady state time. The steady  
30  
31 246 state time corresponds to  $[3\tau, 6\tau]$ . Thus,  $\tau$ , settling time ( $T_s$ ) and steady state time ( $T_{steady}$ ) gives  
32  
33  
34 247 information about dynamic characteristics of heating demand. This dynamic information of building,  
35  
36 248 thus, depends on the transitional attributes of power level and this information is not totally dynamic  
37  
38 249 but pertaining to the appearance of dynamic behavior, so pseudo dynamic name is chosen. Thus,  
39  
40 250 pseudo dynamic is just a lag of transitional attribute information and further depends on time constant  
41  
42 251  $\tau$  or range between settling and steady state of the dynamic building heating characteristics. The  
43  
44 252 simplified pseudo dynamic lag (PDL) is calculated from equation (2), where,  $t_s$  represents the  
45  
46 253 sampling time of building data and  $T_u$  represents the new unknown time which lies between settling  
47  
48  
49 254 and steady state time. The concise value of  $T_u$  depends on dynamics of the heating demand and  
50  
51 255 pseudo dynamic characteristics can be seen from figure (3), where PDL is pseudo dynamic lag.

52  
53  
54  
55  $T_s \leq T_u \leq T_{steady}$ , where  $T_s \in [2\tau, 5\tau]$ ;  $T_{steady} \in [3\tau, 6\tau]$

56 256 
$$\text{PDL} \in \frac{\tau}{t_s} [3, 6] \quad (2)$$

## 257 2.3 Neural Network Model

1  
2  
3 258 The neural network consists of neurons to interconnect the inputs, model parameters and  
4  
5 259 activation function. Each interconnection between the neurons represents model parameters. Input-  
6  
7 260 output mapping in neural network is based on the linear and non-linear activation function. From input  
8  
9 261 and targeted data, model parameters are adjusted to minimize the error i.e. difference between actual  
10  
11 262 values and predicted values produced by the network. Learning/training of data are repeated until  
12  
13 263 there is no significant change in the model parameters and only stops the training. This type of  
14  
15 264 learning approach is called supervised learning since predicted value of the model is guided by actual  
16  
17 265 values.

18  
19  
20 266 There are numerous ANN model like Feed-forward Multilayer Perceptron (MLP), Radial Basis  
21  
22 267 Function (RBF) Network, Recurrent Network and Self-Organizing Maps (SOM) [37]. All of these  
23  
24 268 networks have their own learning algorithm to learn and generalize the network. In this paper, MLP is  
25  
26 269 taken as a neural network model since pseudo dynamic model is not fully dynamic (in time behavior).  
27  
28 270 There are two ways of learning mechanism in the neural network: sequential learning and batch  
29  
30 271 learning. In sequential learning, cost function is computed and model parameters are adjusted after  
31  
32 272 each input is applied to the network. In batch learning, all the inputs are fed to the network before  
33  
34 273 model parameters are updated. In batch learning, model parameter adjustment is done at the end of  
35  
36 274 epoch (one complete representation of the learning process) and for this paper, batch learning is  
37  
38 275 carried out.

39  
40  
41 276 MLP network consists of three layers: input layer, hidden layer and output layer and there can  
42  
43 277 exist more than one hidden layer. However, according to the Kolmogorov's theorem [38], single hidden  
44  
45 278 layer is sufficient to map the function provided suitable hidden neurons and for this paper, single  
46  
47 279 hidden layer is used as shown in figure (5). The hidden layer assists to solve non-linear separable  
48  
49 280 problems.

50  
51  
52 281 Figure 5: Neural Network Architecture

53  
54  
55 282 In figure (5),  $x_i$ ,  $w_k$  and  $y$  represents input neuron which varies from  $i = 0$  to  $i = q$ , hidden  
56  
57 283 neuron which varies from  $k = 0$  to  $k = p$  and output neuron respectively. The  $z^{-1}$  signifies transition  
58  
59  
60 284 lag of 1 and  $z^{-M}$  signifies transition lag corresponding to PDL, where maximum value of  $M$  ( $M_{\max}$ )

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62  
63  
64  
65

285 equals to PDL i.e.  $M_{\max} = \{1,2,\dots,PDL\}$ . The MLP uses logistic function or hyperbolic tangent as a  
286 threshold function in the hidden layer. It has been identified empirically [39] that network using logistic  
287 functions tends to converge slower than hyperbolic tangent activation function in the hidden layer  
288 during the learning phase. Hyperbolic tangent activation functions is chosen in the hidden layer and  
289 pure linear activation function is chosen in the output layer for this paper and hyperbolic tangent  
290 function is shown in equation (3), where  $\theta^T$  represents model parameter with transpose of matrix.  
291 Division of input and output data into learning, validation and testing gives more generalization of  
292 model. Learning data sets are used to learn the behavior of input data and to adjust the model  
293 parameters. Validation data is used to minimize the overfitting. It is not used to adjust the model  
294 parameter but it is used to verify if any increase in accuracy over learning dataset actually yields an  
295 increase in accuracy over dataset that has not learned to the network before. Testing data sets are  
296 used to confirm the actual prediction from neural network model which is unknown to neural network  
297 before. For this paper, data is divided into learning, validation and testing sets. Normalization of input  
298 data is also important for faster convergence to achieve desire performance goal. If input data are  
299 poorly scaled during learning process, there is a risk of inaccuracy and slower convergence. It is, thus,  
300 essential to standardize the input data before applying to neural network. There are various methods  
301 for normalization of input and output variable, and for this paper, normalization with zero mean and  
302 unit standard deviation is done as shown in equation (4). In equation (4),  $\bar{x}$ ,  $X^i$  and  $m$  represents  
303 mean of input variable, overall vector of input variable and number of datasets respectively and thus,  
304 applies similarly for output variable.

$$305 \quad h(\theta^T, x) = \frac{e^{\theta^T x} - e^{-\theta^T x}}{e^{\theta^T x} + e^{-\theta^T x}} \quad (3)$$

$$306 \quad X^i = \frac{x^i - \bar{x}}{\sqrt{\frac{1}{m-1} \sum_i (x^i - \bar{x})^2}} \quad (4)$$

307 The cost function of MLP network is computed in equation (5):

$$308 \quad J(\theta) = \frac{1}{2m} \sum_{l=1}^m [y^{(l)} - y_a^{(l)}]^2 \quad (5)$$

309 where  $y$ ,  $y_a$ ,  $l$  and  $J(\theta)$  represents predicted values produced from the network, actual values of  
 310 given datasets, individual data from  $m$  number of datasets and cost function of the neural network  
 311 model respectively. Further,  $y$  of the network is computed as:

$$y = \sum_{k=1}^p \theta_k h \left( \sum_{i=0}^q \theta_{ki} x_i \right) \quad (6)$$

313 In order to update the model parameters for a higher degree approximation on unknown non-  
 314 linear function for learning process, there are different methods as – gradient descent, Newton's  
 315 method and so on [37]. Gradient descent is too slow for the convergence, and it takes more time to  
 316 compute the hessian matrix in Newton's method as well. Levenberg-Marquardt algorithm is used for  
 317 this paper which takes approximation of hessian matrix in the form of Newton's method and model  
 318 parameter update equation  $\theta_{t+1}$  is given as:

$$\theta_{t+1} = \theta_t - \left[ [L^T L + \mu I]^{-1} L^T J(\theta) \right] \quad (7)$$

320 In equation (7), hessian matrix is approximated as  $[L^T L]$  and gradient is computed as  $L^T J(\theta)$ ,  
 321 where,  $L$  is Jacobian matrix,  $J(\theta)$  is vector of cost function,  $\theta_t$  is initial model parameter,  $\mu$  is  
 322 suitable chosen scalar and  $I$  is identity matrix. Update model parameter, thus, depends on the cost  
 323 function and scalar value  $\mu$ .

### 324 2.3.1 Stopping Criteria

325 There are different criteria for stopping the neural network model. For this paper, the stopping  
 326 criteria depend on number of epochs to learn the network, performance goal, maximum range of  $\mu$   
 327 and maximum failures in the validation. The performance goal (PG) is given as:

$$PG = 0.01 \sum_{l=1}^m y_a^{(l)} \quad (8)$$

329 The maximum failures in validation or accuracy over validation datasets is defined to stop the  
 330 learning process if the accuracy of learning datasets increase and validation accuracy stays same or  
 331 decrease.

### 332 2.3.2 Model Performance

1  
2  
3 333 Performances of models are characterized by mean square error (MSE) and coefficient of  
4  
5 334 correlation ( $R^2$ ). The MSE and  $R^2$  can be calculated as:

6  
7  
8  
9  
10 335 
$$\text{MSE} = \frac{\sum_{l=1}^m [y^{(l)} - y_a^{(l)}]^2}{m} \quad (9)$$

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12  
13  
14  
15  
16 336 
$$R^2 = \frac{\sum_{l=1}^m [y^{(l)} - y_a^{(l)}]^2}{\sum_{l=1}^m (y_a^{(l)})^2} \quad (10)$$

### 21 337 2.3.3 Degree of Freedom Adjustment

22  
23  
24 338 One of the issues of neural network model is over learning of the network. With increase of  
25  
26 339 hidden neurons, model performance can be increased, but, it will lead neural network to over learning.  
27  
28 340 Validation accuracy and degree of freedom (DOF) adjustments are done in this paper to avoid over  
29  
30 341 fitting. Number of learning equations that model could deliver are given by equation (11), where  $L_e$  is  
31  
32 342 learning equations of the network and  $L_y$  is length of vector output neurons ( $y$ ), and in this case  
33  
34  
35  
36 343 equal to 1 since there is only heating demand load.

37  
38  
39 344 
$$L_e = m * L_y \quad (11)$$

40  
41  
42 345 The number of model parameters for a single hidden layer MLP neural network are given by  
43  
44 346 the equation (12), where  $L_\theta$ ,  $L_x$  and  $L_w$  represents number of model parameters, vector length of  
45  
46  
47 347 input neurons ( $x_i$ ) and vector length of hidden neurons ( $w_k$ ) respectively.

48  
49  
50  
51 348 
$$L_\theta = (L_x + 1) * L_w + (L_w + 1) * L_y \quad (12)$$

52  
53  
54 349 DOF of neural network model is the difference between number of learning equations and  
55  
56 350 number of model parameters in the network. It should be always  $\gg 1$  and depends on the optimum  
57  
58 351 size of hidden neurons. DOF and maximum hidden neurons are given by equation (13) and (14),

352 where,  $\delta$  represents the scalar constant value and depends on DOF required for design and  $W_{\max}$  is  
 353 the maximum hidden neurons.

$$354 \quad \text{DOF} = L_e - L_\theta \quad (13)$$

$$355 \quad W_{\max} \cong \frac{1}{\delta} \frac{(L_\theta - L_y)}{(L_x + L_y + 1)} \quad (14)$$

356 Modified performance goal according to degree of freedom adjustment is given as:

$$357 \quad \text{PG} = \frac{0.01 \text{DOF} \sum_{l=1}^m y_a^{(l)}}{L_e} \quad (15)$$

358 Model performance is also further modified based on degree of freedom adjustment. The  
 359 modified MSE and  $R^2$  can be calculated as:

$$360 \quad \text{MSE}_{\text{modified}} = \frac{L_e \sum_{l=1}^m [y^{(l)} - y_a^{(l)}]^2}{\text{DOF} * m} \quad (16)$$

$$361 \quad R^2_{\text{modified}} = \frac{L_e \sum_{l=1}^m [y^{(l)} - y_a^{(l)}]^2}{\text{DOF} \sum_{l=1}^m (y_a^{(l)})^2} \quad (17)$$

362 For each hidden neurons, optimal  $\text{MSE}_{\text{modified}}$  and maximum  $R^2_{\text{modified}}$  for learning and  
 363 validation are calculated from the different initialized random parameters. For different number of  
 364 hidden neurons,  $R^2_{\text{modified}}$  and  $\text{MSE}_{\text{modified}}$  for each model is performed for learning and validation,  
 365 and based on it, optimal configuration of model is identified for the final prediction.

## 366 2.4 Orthogonal Arrays

367 It is essential to know whether schedule of occupancy profile and operational characteristics  
 368 obtained from ESCOs is reliable for the robust design of pseudo dynamic model. Occupancy profile  
 369 and operational characteristics transition period, thus, plays an important role in the model

370 performance and if all these transition period are consider for finding the best robust model, it takes  
1  
2 371 long time to compute. Orthogonal arrays (OA) identify the main effects with minimum number of trials  
3  
4 372 to find the best design. These are applied in various fields: mechanical and aerospace engineering  
5  
6 373 [40], electromagnetic propagation [41] and signal processing [42] for the robust design model.  
7

8  
9 374 The orthogonal array allows the effect of several parameters to find best design with given  
10  
11 375 different levels of parameters. It can be defined as matrix with column representing number of  
12  
13 376 parameters with different settings to be studied and rows representing number of experiments. In  
14  
15 377 orthogonal arrays, parameters are called factors and parameter settings are called levels. In general,  
16  
17 378  $OA(N, k, s, t)$  is used to represent the orthogonal arrays, where  $N$ ,  $k$ ,  $s$  and  $t$  represents number  
18  
19 379 of experiments, number of design parameters, number of levels and strength. There are different  
20  
21 380 methods as Latin square [43]; Juxtaposition [44]; Finite geometries [45] etc... to create orthogonal  
22  
23 381 arrays with different strength and levels. Orthogonal arrays with different number of design parameter,  
24  
25 382 level, and strength are available from OA databases or libraries. The orthogonal arrays used for this  
26  
27 383 paper is taken from OA library [46].  
28  
29

### 30 384 **3. Case Study**

31  
32

33 385 The methodology is applied for case study at Ecole des Mines de Nantes, French Institution.  
34  
35 386 The building has floor area of 25,000 m<sup>2</sup>. It has 600 students and 200 employees. The building  
36  
37 387 consists of 120 research and administration rooms, 30 class rooms, 3 laboratories, and 8 seminar  
38  
39 388 halls. Class rooms have different sizes and can accommodate to 18 to 28 students. The 2 big seminar  
40  
41 389 halls can be occupied by 250 students and 6 small seminar halls can be occupied by 80 students.  
42  
43 390 Each floor area of the laboratory is 600 m<sup>2</sup>.  
44  
45

46 391 The data is taken from data acquisition system and consists of day/month/time, solar radiation,  
47  
48 392 outside air temperature and heating demand from mid of January to February 2013 with sampling  
49  
50 393 interval of 15 minutes. The 70% of data (outside temperature, solar radiation and heating demand as  
51  
52 394 shown in figure 5) are used for learning phase i.e.  $m$  in mathematical equation in neural network, see  
53  
54 395 section 2.3, equivalent to 19 days with 15 minute sampling time, and each 15% of data (4 days with 15  
55  
56 396 minute sampling time) is used for validation and testing phase. [Outside temperature taken for this](#)  
57  
58  
59  
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62  
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397 study has minimum, average and maximum value of 1.2 °C, 8.95 °C and 15.3 °C respectively. Global  
1 398 solar radiation has an average and maximum value of 7 W/m<sup>2</sup> and 438 W/m<sup>2</sup> respectively.  
2  
3

4 399 The simplified/theoretical occupancy profile and operational heating power level characteristics  
5  
6 400 for working and off-days for 24 hours is shown in figure (6) and (7).  
7

8  
9 401 **Figure 6: Occupancy profiles for working and off-day**  
10

11  
12 402 **Figure 7: Operational heating power level characteristics for working and off-day**  
13

14  
15 403 Power demand and occupancy profile during working day is depicted from figure (8). From  
16 404 figure (8), occupancy profile almost gives information about power demand characteristics, however,  
17  
18 405 from 18 hour onwards, power demand characteristics is not accordance with occupancy profile. Thus,  
19  
20 406 it further shows that simplified occupancy profile is not enough to characterize the heating demand.  
21  
22

23  
24 407 **Figure 8: Heating power demand and occupancy profile during working days**  
25

26  
27 408 Different neural network models are designed based on climate variables (outside temperature  
28  
29 409 and solar radiation), work/off day information, occupancy profile and operational characteristics as  
30  
31 410 shown in figure (5). For this case study, 10 represent working day and 5 represent off day information  
32  
33 411 (work/off day) to the input of neural network model. Static neural network model 1 consists of  
34  
35 412 operational characteristics and occupancy profile, external temperature and solar radiation as input  
36  
37 413 variables and heating power demand as an output variable, and thus, vector length of input neurons  
38  
39 414 ( $L_x$ ) in equation (12) equals to 5. Model 2 comprises additional transitional characteristics in model 1  
40  
41 415 and vector length of input neurons ( $L_x$ ) in equation (12) equal to 6. For this case study the sampling  
42  
43 416 time ( $t_s$ ) of real building data is 15 minutes, settling time ( $T_s$ ) is estimated approximately 45 minutes  
44  
45 417 and steady state time ( $T_{steady}$ ) is approximately 1 hour. The PDL, thus, is calculated from equation (2),  
46  
47  
48 418 where PDL corresponds to settling and steady state time is nearly equal to 3 and 4 respectively. Since  
49  
50 419 pseudo dynamic model depends on transition lag of operational heating power level and building  
51  
52 420 dynamic characteristics, PDL is varied from 3-4, and to understand the phenomena of pseudo dynamic  
53  
54 421 lag, PDL is varied from 1-4. Model 3 comprises model 2 with additional parameters of one PDL i.e. i.e.  
55  
56 422  $L_x$  equals to 7; model 4 consists model 2 with additional parameters of two PDL i.e.  $L_x$  equals to 8;  
57  
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423 model 5 includes model 2 with additional parameters of three PDL i.e.  $L_x$  equals to 9 and model 6  
424 comprises model 2 with additional parameters of four PDL in the transitional characteristics i.e.  
425  $L_x$  equals to 10. Transitional and pseudo dynamic characteristic with four lags during working day is  
426 shown in figure (9). Transition level in figure (9) is calculated from equation (1) and for this case study,  
427 25 is chosen for each  $\beta_0$  and  $\Delta\beta$ . In figure (9), lag 0 means static model which contains transition  
428 attributes, lag 1 means pseudo dynamic model with transition lag 1 (PDL=1), lag 2 means pseudo  
429 dynamic model with transition lag 2 (PDL=2) and so on. Further, effects of transitional and pseudo  
430 dynamic effects on the heating demand can be understood from figure (10). It is clear that the  
431 information hidden in heating demand which climate variables could not answer can be justify from  
432 transitional and pseudo dynamic attributes of operational characteristics. The summary of models is  
433 shown in table (2).

434 [Figure 9: Transitional and pseudo dynamic characteristics during working day](#)

435 [Figure 10: Pseudo dynamic transitional effects on heating demand](#)

436 [Table 2: Summary of models](#)

437 For each model, cost function  $J(\theta)$  in equation (5) is computed iteratively up to 1000 for each  
438 of the minimum and maximum number of hidden neurons. The maximum number of hidden neurons is  
439 calculated from equation (14), where  $\delta$  is chosen 8 as it gives the flexibility in the degree of model  
440 parameters. Thus, three minimum hidden neurons are chosen as 3 for this case study. Hidden  
441 neurons length ( $L_w$ ), thus, is varied from 3 to  $W_{\max}$ . Performance of model at each iteration (number  
442 of epochs) is computed from equation (16) and (17) and model parameters are updated based on  
443 equation (7), where initial value of  $\mu$  is chosen as 0.01 and its value is increased with a factor of 10  
444 and decreased with a factor of 0.1. The maximum value of  $\mu$  is chosen as 1e10. Neural network  
445 model in this study will be stopped if the number of epochs reached to 1000 and performance goal  
446 reached the value given by equation (15).

447 Under the scope of study (see subsection 2.1), the accuracy on the number of occupants are  
448 not relevant, however, it is essential to know inside the sampling time, when the staff and students  
449 come and leaves the buildings. It is necessary to check occupancy and operational power level

450 characteristics provided by ESCOs are right or not for robust design model. And, the main controlling  
1 451 factors for robust design model are the transition schedule of occupancy and operational  
2 452 characteristics. From figure (6), it is clear that there is no transition of occupancy during off-day, but  
3 453 there is transition of occupancy during the interval at 8 hour, 12 hour, 13:30 hour and 17:45 hour and  
4 454 these are represented by t1, t2, t3 and t4 factors respectively. Similarly, there is a transition of  
5 455 operational characteristics for working and off day as shown in figure (7) and these transition factors  
6 456 are represented by t5, t6, t7 and t8 for working day for 6 hour, 12 hour, 14 hour and 20 hour; t9 and  
7 457 t10 for off day for 6 hour and 20 hour. Since the sampling interval taken for this case study is 15  
8 458 minutes, three levels are used for orthogonal arrays so that the model will represent the 15 minutes  
9 459 ahead and before from occupancy and operational characteristics schedule period. The summary of  
10 460 control factors and their levels are shown in table (3), where OSW represents occupancy schedule at  
11 461 work day, OCSW represents operational characteristics schedule at work day and OCSO represent  
12 462 operational characteristics schedule at off day.

27 463 **Table 3: Summary of control factors and their levels**

28  
29  
30 464 Thus, there are 10 factors and 3 levels that govern the robustness of the model and if the full  
31 465 factorials are used to generalize the model, it takes  $3^{10} = 59049$  experiments. The orthogonal arrays  
32 466 reduce the number of experiments to 729 with 5 strengths. OA (729,10,3,5) is applied to the proposed  
33 467 pseudo dynamic model in this case study.

#### 38 39 468 **4. Result and Discussion**

40  
41  
42 469 Optimal configuration of the model is based on maximum  $R^2_{modified}$  and minimum  
43 470  $MSE_{modified}$  from different randomized parameters. For each hidden neuron in the model, five  
44 471 randomized parameters are assigned for the learning phase and based on it, the neurons with  
45 472 minimum  $MSE_{modified}$  and maximum  $R^2_{modified}$  for learning and validation are chosen from randomized  
46 473 parameters. Optimal configuration of each model is chosen from maximum  $R^2_{modified}$  and  
47 474 minimum  $MSE_{modified}$  model performance from learning and validation datasets for different hidden  
48 475 neurons. Figure (11) and (12) shows  $R^2_{modified}$  and  $MSE_{modified}$  performance for learning, validation  
49 476 and testing for different hidden neuron sizes of model 5 and from this optimal configuration is chosen

477 from the best performance model. It is clear from figure (11) and (12) that the maximum  $R^2_{modified}$   
478 and minimum  $MSE_{modified}$  performance is achieved in hidden neuron size 13 and which is the optimal  
479 configuration of the model. It can also be noticed that although  $R^2$  testing performance increases for  
480 hidden neuron size 15,  $R^2$  for validation and learning does not increase optimally. The model 5 is just  
481 an example and similarly, the process is repeated for each model to find the optimal configuration of  
482 the neural network model. The optimal configurations of the different neural network model are  
483 summarized in table (4).

484 Figure 11: Coefficient of correlation performance (Model 5)

485 Figure 12: Mean Square Error performance (Model 5)

486 Table 4: Optimal configuration of models

487 Table (4) shows that with static neural network model 1, best  $R^2_{modified}$  for learning and  
488 validation can be obtained up to 0.82 and 0.81. From this, it is clear that occupancy profile and  
489 operational characteristics are not enough to determine and generalize the unknown function of the  
490 building heating demand. As transitional attributes of operational characteristic is introduced in model  
491 2,  $R^2_{modified}$  model performance increases significantly from 0.82 to 0.87 for learning phase and from  
492 0.81 to 0.85 for validation phase and correspondingly  $MSE_{modified}$  decreases in contrast to model 1.  
493 Pseudo dynamic transitional attributes in model 3 and time constant  $\tau$  in model 4 leads increase in  
494 model performance. Further, dynamics of settling time and steady state plays an important role in  
495 characterizing the neural network model. It is seen that  $R^2_{modified}$  performance increases from 0.87 to  
496 0.89 for learning and 0.85 to 0.87 for validation in model 5 compare to model 2 although transition  
497 attributes is introduce in model 2. In addition, hidden neuron size is also reduces from 19 to 13.  
498 Moreover, it is distinguish that learning and validation performances remained the same in the model 6  
499 compared to model 5. The optimal choice of the model, thus, lies in between settling and steady state  
500 time.

501 It can be further view that model 5 and model 6 show reasonable and consistent model  
502 performances. However, minimum hidden neuron size and maximum learning criteria is essential for

503 the overall network generalization. Since the hidden neurons size decreases from 13 to 9 and model  
1  
2 504 performance  $R^2_{modified}$  remained the same (0.89) in model 6 comparing to model 5, model 6 is  
3  
4 505 chosen as the best configuration of the overall models. The optimal choice of the model 5 and model 6  
5  
6 506 can be delineated by the error in percentage of energy consumption (kWh) in actual and prediction for  
7  
8 507 the learning and validation phase. Heating energy consumption error in actual and prediction in  
9  
10 508 learning phase in Model 6 is 0.02% compare to 0.32% in Model 5. For validation phase, heating  
11  
12 509 energy consumption error is 2.39% in Model 6 compare to 2.57% in Model 5. From this energy  
13  
14 510 consumption error, it is clear that there is a small heating energy consumption error in Model 6  
15  
16 511 compare to Model 5 during the learning and validation phase. So, one can conclude that Model 6 can  
17  
18 512 be chosen as optimal configuration of the overall model. The model 6, thus, bridges the gap between  
19  
20 513 static and dynamic neural network model in the sense that it is better than static model and increases  
21  
22 514 the performance comparable to dynamic neural network model.

25 515 For the robustness of pseudo dynamic model, orthogonal arrays are applied to determine the  
26  
27 516 highest coefficient of correlation for learning and validation for the optimum 9 hidden neuron size of  
28  
29 517 model 6. Table (5) shows OA(729,10,3,5) and coefficient of correlation for learning and validation  
30  
31 518 phase. It is clear from table (5) that the schedule taken from the ESCOs is from experiment 1 and from  
32  
33 519 the orthogonal arrays, the optimal schedule that fits the best for model 6 is experiment 398. The  
34  
35 520 orthogonal arrays, thus, ensures that there is transition in occupancy in 7:45 hour, 12 hour, 13:45 hour  
36  
37 521 and 18 hour instead of 8 hour, 12 hour, 13:30 hour and 17:45 hour period in the existing case  
38  
39 522 respectively. There is also a transition in 5:45 hour, 11:45 hour, 14 hour and 17:45 hour instead of 6  
40  
41 523 hour, 12 hour, 14 hour and 17:45 hour for working day; 5:45 hour and 20 hour instead of 6 hour and  
42  
43 524 20 hour in off days for operational characteristics. The coefficient of correlation after the orthogonal  
44  
45 525 array design is 0.90 for learning, 0.88 for validation and 0.86 for training phase. Nevertheless, other  
46  
47 526 issue of overall model is that it is difficult to increase the coefficient of correlation beyond 0.90 and this  
48  
49 527 is due to the sampling time of 15 minutes. With short sampling time, it is very difficult to learn the  
50  
51 528 datasets which changes in 15 minutes sample, nonetheless, for good generalization of the model,  
52  
53  
54 529  $R^2_{modified}$  value of 0.90 during the learning phase is always acceptable.

57 530 Table 5: OA (729,10,3,5) and coefficient of correlation for learning and validation for model 6  
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531 Coefficient of correlation of linear regression obtained from neural network model in the actual  
1  
2 532 and prediction of heating demand for learning, validation and testing phase of Model 6 after optimum  
3  
4 533 orthogonal array design are 0.95, 0.95 and 0.93 respectively. The prediction of heating demand for  
5  
6 534 model 6 after optimum orthogonal array design during validation phase is shown in figure (13).  
7  
8 535 Prediction gives the power heating demand and the area under the curve gives the heating energy  
9  
10 536 demand. From figure (13), it is clear that heating demand tremendously increases approximately 990  
11  
12 537 kW during third and fourth day and pseudo dynamic model is able to predict and learn the behavior.  
13  
14 538 However, there is a fluctuation in the power demand in the morning for each consecutive 4 days and it  
15  
16 539 is difficult to learn datasets which transits rapidly in actual power demand. The prediction of heating  
17  
18 540 demand for model 6 during testing phase after optimum orthogonal array design is shown in figure  
19  
20 541 (14). It is vivid that pseudo dynamic model is able to predict heating demand, however during the third  
21  
22 542 day, the pseudo dynamic model is not able to meet 1.1 MW of heating demand. This is due to the fact  
23  
24 543 that neural network does not learn this threshold maximum heating demand in the learning phase as  
25  
26 544 this kind of information is not available in the database. This data, thus, needs to be improved in the  
27  
28 545 learning phase through feature extraction techniques. Nonetheless, pseudo dynamic model (model 6)  
29  
30 546 prediction is in accordance to the actual target except for some rapid transits in the actual target. To  
31  
32 547 sum up, pseudo dynamic transition attributes in model 6 after orthogonal array design leads best  
33  
34 548 prediction of heating demand.

35  
36  
37 549 Figure 13: Prediction of heating demand in model 6 during validation phase (after optimum orthogonal  
38  
39 550 array design)

40  
41  
42 551 Figure 14: Prediction of heating demand in model 6 during testing phase (after optimum orthogonal  
43  
44 552 array design)

#### 47 553 **4. Conclusion**

48  
49  
50 554 This paper introduces pseudo dynamic transitional model for the building heating demand  
51  
52 555 prediction in a short time horizon using artificial neural network. Occupancy profile and operational  
53  
54 556 heating power level characteristics are included in the model. Dynamic characteristic of the building is  
55  
56 557 included in the model for the determination of pseudo dynamic transition lag. Settling time and steady  
57  
58 558 state time of the heating demand give an increment in precision of the model, however, choice of  
59  
60 559 model depends on their actual time between settling and steady state. The results were based on case  
61  
62  
63  
64  
65

560 study where occupancy profile is already known and results may vary for more fluctuating occupancy  
1 561 buildings. Coefficient of correlation increases from 0.82 to 0.89 for learning, 0.81 to 0.87 for validation  
2  
3 562 and 0.61 to 0.85 for testing in pseudo dynamic comparing to static neural network model. Also, the  
4  
5 563 size of hidden neuron is further reduced, which reduces complexities and increases generalization of  
6  
7 564 the model. Moreover, minimum energy consumption error is achieved in pseudo dynamic model as  
8  
9 565 0.02% for learning and 2.57% for validation phase. Further, orthogonal array is applied to optimal  
10  
11 566 pseudo dynamic model to confirm the schedule of occupancy profile and operational level  
12  
13 567 characteristics, and robustness of the model. The orthogonal array design leads to the increases in  
14  
15 568 coefficient of correlation in pseudo dynamic model and confirmed the new schedule of the occupancy  
16  
17 569 profile and operational level characteristics. The major contribution of this paper, thus, is the  
18  
19 570 introduction of transition and novel time dependent attributes of operational heating power level  
20  
21 571 characteristics, which is the dominant factor for building heating demand. Also, orthogonal array  
22  
23 572 design in the model makes flexibility in cross checking the schedule of occupancy profile and  
24  
25 573 operational heating power level characteristics obtained from ESCOs to design the robust model. The  
26  
27 574 prediction is in short time horizon (4 days) with sampling interval of 15 minutes and thus useful for  
28  
29 575 dynamic control of building heating demand.  
30  
31  
32

33 576 Further, research will be focused towards the feature extraction of data before learning phase of  
34  
35 577 the neural network so that abnormalities in the data can be corrected in the learning phase. Also  
36  
37 578 adaptive and real time learning criteria with seasonal behaviour will be studied.  
38  
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#### 40 579 **Acknowledgement**

41  
42  
43 580 This research has been done in collaboration with Ecole des Mines, Nantes, Technische Universiteit  
44  
45 581 Eindhoven and VEOLIA Environnement Recherche et Innovation, funded through Erasmus Mundus  
46  
47 582 Joint Doctoral Programme SELECT+, the support of which is gratefully acknowledged.  
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#### 689 Appendix A

690 The influence of input variables on the model output is evaluated based on the correlation analysis.  
 691 Correlation measures the strength and weakness of linear relationship between two variables. There  
 692 are several coefficients that measure the correlation degree and Pearson's correlation coefficient is  
 693 used to determine the input variables relevance for this paper. Pearson's correlation coefficient is  
 694 calculated by dividing covariance of two variables by product of their standard deviation as shown in  
 695 equation (A.1 – A.2), where  $r$  represents Pearson's correlation coefficient. In equations (A.1-A.2),  
 696  $\text{cov}(xy)$  is covariance which represents strength of linear relationship between two variables  $x$   
 697 and  $y$ ;  $\bar{x}$  and  $\bar{y}$  are mean values of variables  $x$  and  $y$ ;  $s_x$  and  $s_y$  are standard deviations of  
 698 variables  $x$  and  $y$ ; and  $n$  is the number of data.

$$699 \quad r = \frac{\text{cov}(xy)}{s_x s_y} \quad (\text{A.1})$$

$$700 \quad \text{cov}(xy) = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y}) \quad (\text{A.2})$$

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3 701 The correlation coefficients can range from -1 to +1:  
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5 702  $r = 1$  : perfect positive linear correlation  
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7 703  $r = -1$  : perfect negative linear correlation  
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9 704  $0.1 < |r| < 0.25$  : small positive linear correlation  
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11 705  $0.25 < |r| < 0.6$  : medium positive linear correlation  
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13 706  $0.6 < |r| < 1$  : strong positive linear correlation  
14

15 707  $-1 < r < 0$  : negative linear correlation  
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19 708 Climatic conditions (outside temperature and solar radiation), operational power level characteristics  
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21 709 and approximate occupancy profile are used to evaluate the relevance variables that affect building  
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23 710 heat demand based on case study data. Other variables pseudo dynamic transitional attributes, which  
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25 711 signifies the dynamics of building characteristics is not consider for relevance variable determination  
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27 712 since it only signifies time and phase interval of heating power transition.  
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33 713 Results show the linear coefficient of correlation of outside air temperature, solar radiations,  
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35 714 occupancy profile and operational power level characteristics with the heat load are -0.84, -0.40, 0.32  
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37 715 and 0.35 respectively. Results, thus, signifies that climatic conditions (outside temperature and solar  
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39 716 radiations) are relevant input variables to predict the heat load. Also, it is clearer that occupancy profile  
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41 717 and operational power level characteristics has medium positive correlation with heat load and shows  
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43 718 relevance to characterize the heat demand behaviour.  
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Table 1 : Summary of variables and application models in the literature

Author and Year	Type of Model	Input Variable of Model									Horizon of Prediction	Type of Applications for Buildings
		Climate Variables			Global Solar Radiation	Wind Speed	Relative Humidity	Occupancy Profile	Operational Characteristics	Other Parameters		
		Ambient	Dry Bulb	Wet Bulb								
Girardin et al. [12] (2009)	Statistical	√								√ (1*)	Annually	80 Residential (heating and cooling)
Yao et al. [13] (2005)	Thermal and Statistical	√								√ (2*)	Daily	Residential (space heating)
Catalina et al. [14] (2008)	Regression	√			√						Monthly	Residential
Wan et al. [15] (2012)	Regression		√	√	√					√ (3*)	Monthly & Yearly	Office (heating and cooling)
Dong et al. [17] (2005)	SVM		√		√		√				Monthly	4 Buildings (total energy consumptions)
Kalogirou et al. [19] (2001)	Static NN □				√		√				Daily	9 Buildings (heating and cooling)
Neto et al. [20] (2008)	Static NN □		√		√		√				Daily	Office (3000 m2)
Shilin et al. [21] (2010)	Static NN □	√									Daily	Residential (cooling power)
Mihalakakou et al. [22] (2002)	Static NN	√(4*)			√						Hourly	Residential (200 m2)
Ekici et al. [23] (2009)	Static NN									√ (5*)	Hourly	Heating Energy of Buildings
Dombayci [24] (2010)	Static NN									√ (6*)	Hourly	Residential (heating energy)
Gonzalez et al. [25] (2005)	Static NN	√								√ (7*)	Hourly	Electrical load
Popescu et al. [26] (2009)	Static NN				√	√	√			√ (8*)	Hourly	8 Buildings
Kato et al. [27] (2008)	Dynamic NN	√(9*)									Hourly	District (heating energy)
Kalogirou et al. [28] (2000)	Dynamic NN									√ (10*)	Hourly	Passive solar buildings
Li et al. [18] (2010)	SVM		√(11*)		√(11*)		√				Hourly	Office building and library
Sun et al. [29] (2013)	Regression	√			√		√	√ (12*)		√ (13*)	Hourly	Cooling load for high rise buildings (440,000 m2)
Yun et al. [30] (2012)	Autoregressive with exogeneous	√	√		√	√	√	√			Hourly	Small building for heating load (464 m2)
Leung et al. [32] (2012)	Static NN		√	√	√	√		√ (14*)	√	√ (15*)	Hourly & Daily	Office (space electrical power demand)
Duanmu et al. [10] (2013)	Physical	√			√	√	√			√ (16*)	Hourly	Cooling load of buildings

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8 Remarks:

- 1\*: Nominal Temperature of heating, cooling and hot water system; Threshold heating and cooling temperature
- 2\*: Appliances Model
- 3\*: Climate Index based on principal component
- 4\*: Multiple lag output predictions of ambient air temperature
- 5\*: Transmittivity, orientation and insulation thickness
- 6\*: Heating degree hour method
- 7\*: Predict value of temperature, present electricity load, hour and day
- 8\*: Outside temperature and mass flow rate in previous 24 hour, hot water temperature
- 9\*: Highest and Lowest open air temperature
- 10\*: Season, insulation, wall thickness, heat transfer coefficient
- 11\*: Multiple lag of dry bulb temperature and solar radiation
- 12\*: Reference day of each day based on occupancy schedule
- 13\*: Correlated weather data based on reference day and accuracy of calibrated prediction error of previous 2 hours
- 14\*: Occupancy profile represented by space electrical power demand
- 15\*: Clearness of sky, rainfall, cloudiness conditions
- 16\*: Physical and geometrical parameters, hourly cooling load factor

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Table 2: Summary of models

Model No.	Type of Model	Input Variables	Remarks
Model 1	Static	Climates, occupancy profile and operational characteristics	No Lag
Model 2	Static	Model 1 with transitional characteristics	No Lag
Model 3	Pseudo Dynamic	Model 2 with pseudo dynamic transition with delay	Lag 1
Model 4	Pseudo Dynamic	Model 2 with pseudo dynamic transition in t	Lag 2
Model 5	Pseudo Dynamic	Model 2 with pseudo dynamic transition in settling time	Lag 3
Model 6	Pseudo Dynamic	Model 2 with pseudo dynamic transition in steady state time	Lag 4

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Table 3: Summary of control factors and their levels

Factors	Levels		
	1	2	3
OSW at 8 hour (f1)	t1-15 min	t1	t1+15 min
OSW at 12 hour (f2)	t2-15 min	t2	t2+15 min
OSW at 13:30 hour (f3)	t3-15 min	t3	t3+15 min
OSW at 17:45 hour (f4)	t4-15 min	t4	t4+15 min
OCSW at 6 hour (f5)	t5-15 min	t5	t5+15 min
OCSW at 12 hour (f6)	t6-15 min	t6	t6+15 min
OCSW at 14 hour (f7)	t7-15 min	t7	t7+15 min
OCSW at 20 hour (f8)	t8-15 min	t8	t8+15 min
OCSO at 6 hour (f9)	t9-15 min	t9	t9+15 min
OCSO at 20 hour (f10)	t10-15 min	t10	t10+15 min

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Table 4: Optimal configuration of models

Model	Hidden Neurons	Coefficient of Correlation			Mean Square Error		
		Learning	Validation	Testing	Learning	Validation	Testing
Model 1	10	0.82	0.81	0.61	0.18	0.18	0.40
Model 2	19	0.87	0.85	0.80	0.13	0.15	0.21
Model 3	7	0.88	0.86	0.75	0.12	0.14	0.25
Model 4	9	0.89	0.87	0.82	0.12	0.13	0.18
Model 5	13	0.89	0.87	0.83	0.11	0.13	0.18
Model 6	9	0.89	0.87	0.85	0.11	0.13	0.15

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Table 5: OA(729,10,3,5) and coefficient of correlation for learning and validation for model 6

Experiment	Element	f1	f2	f3	f4	f5	f6	f7	f8	f9	f10	Coefficient of Correlation		
												Learning	Validation	Testing
1		2	2	2	2	2	2	2	2	2	2	0.89	0.87	0.85
2		1	2	2	2	2	2	2	1	1	1	0.89	0.88	0.81
3		3	2	2	2	2	2	2	3	3	3	0.90	0.86	0.76
4		2	1	2	2	2	2	3	2	1	3	0.89	0.86	0.79
5		1	1	2	2	2	2	3	1	3	2	0.89	0.87	0.78
6		3	1	2	2	2	2	3	3	2	1	0.89	0.88	0.79
7		2	3	2	2	2	2	1	2	3	1	0.89	0.87	0.83
8		1	3	2	2	2	2	1	1	2	3	0.89	0.87	0.84
9		3	3	2	2	2	2	1	3	1	2	0.90	0.86	0.85
10		2	2	1	2	2	2	3	1	2	1	0.89	0.87	0.76
11		1	2	1	2	2	2	3	3	1	3	0.89	0.87	0.67
12		3	2	1	2	2	2	3	2	3	2	0.89	0.87	0.67
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...		.	.	.	.	.	.	.	.	.	.	.	.	.
394		2	3	1	3	1	1	3	3	3	3	0.89	0.87	0.80
395		1	3	1	3	1	1	3	2	2	2	0.90	0.87	0.76
396		3	3	1	3	1	1	3	1	1	1	0.90	0.87	0.76
397		2	2	3	3	1	1	2	2	2	3	0.89	0.88	0.81
398		1	2	3	3	1	1	2	1	1	2	0.90	0.88	0.86
399		3	2	3	3	1	1	2	3	3	1	0.90	0.87	0.70
400		2	1	3	3	1	1	3	2	1	1	0.90	0.87	0.77
401		1	1	3	3	1	1	3	1	3	3	0.89	0.88	0.84
402		3	1	3	3	1	1	3	3	2	2	0.87	0.88	0.74
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725		1	1	3	3	3	3	2	1	2	3	0.89	0.87	0.80
726		3	1	3	3	3	3	2	3	1	2	0.90	0.87	0.84
727		2	3	3	3	3	3	3	2	2	2	0.90	0.87	0.80
728		1	3	3	3	3	3	3	1	1	1	0.89	0.88	0.78
729		3	3	3	3	3	3	3	3	3	3	0.89	0.88	0.61

Figure 1

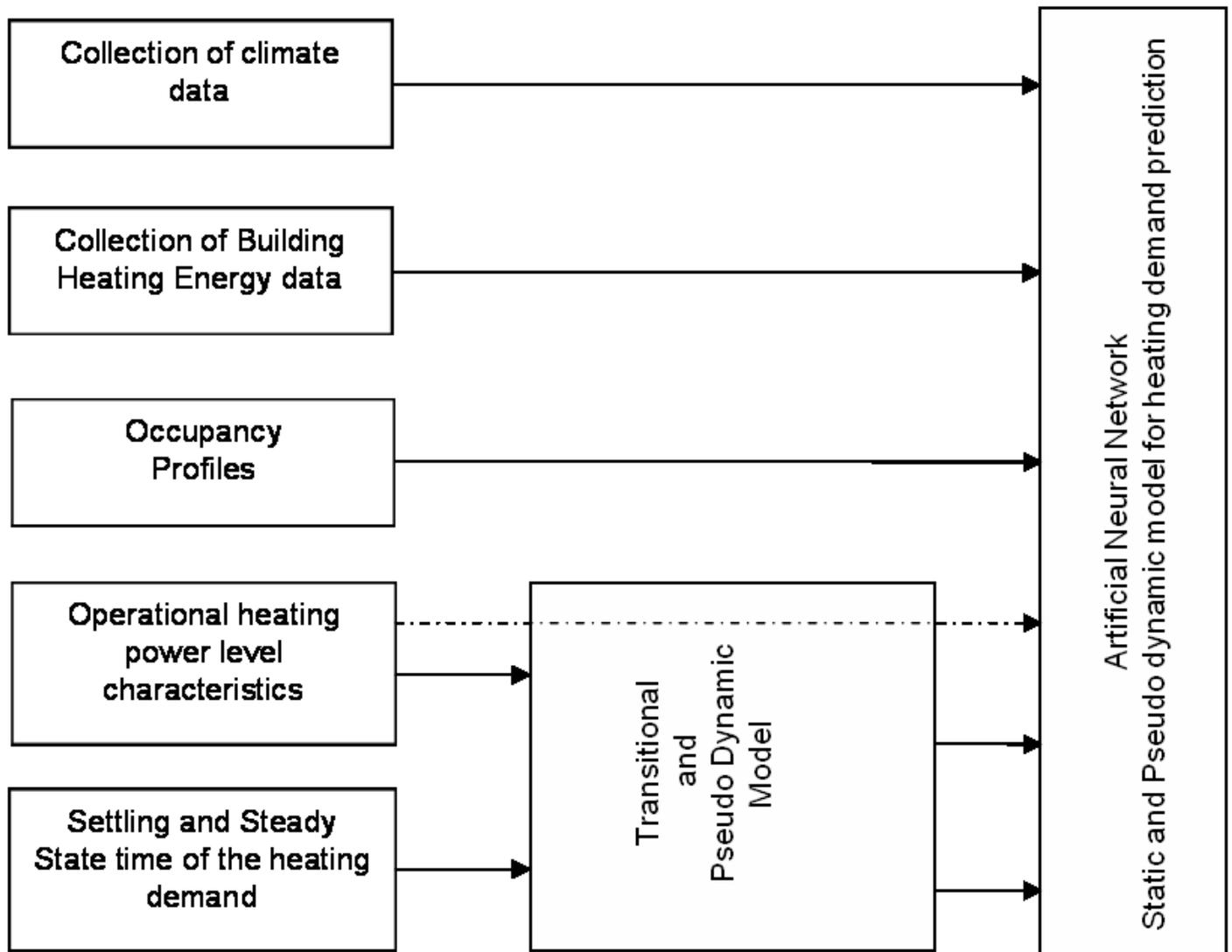


Figure 2

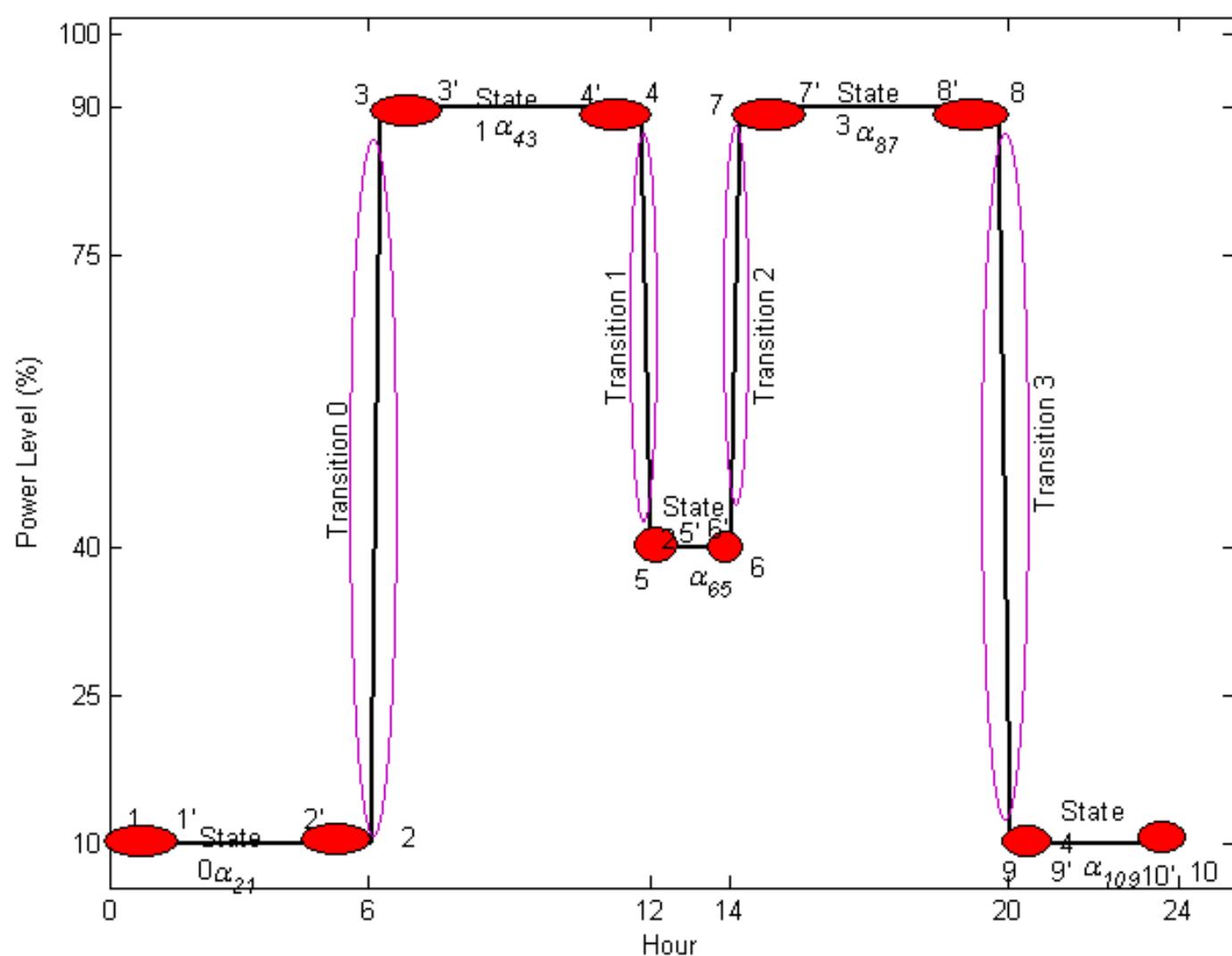


Figure 3

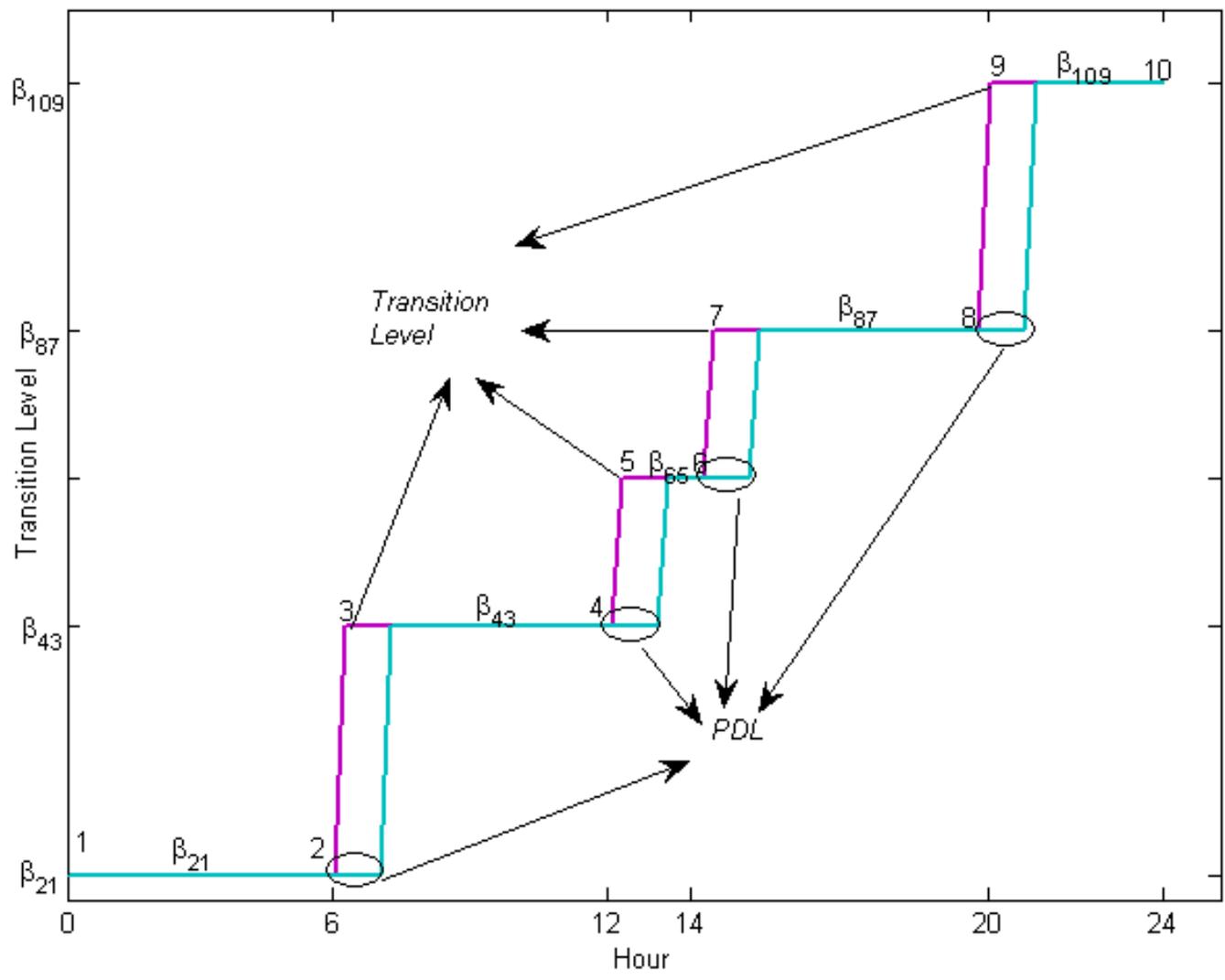


Figure 4

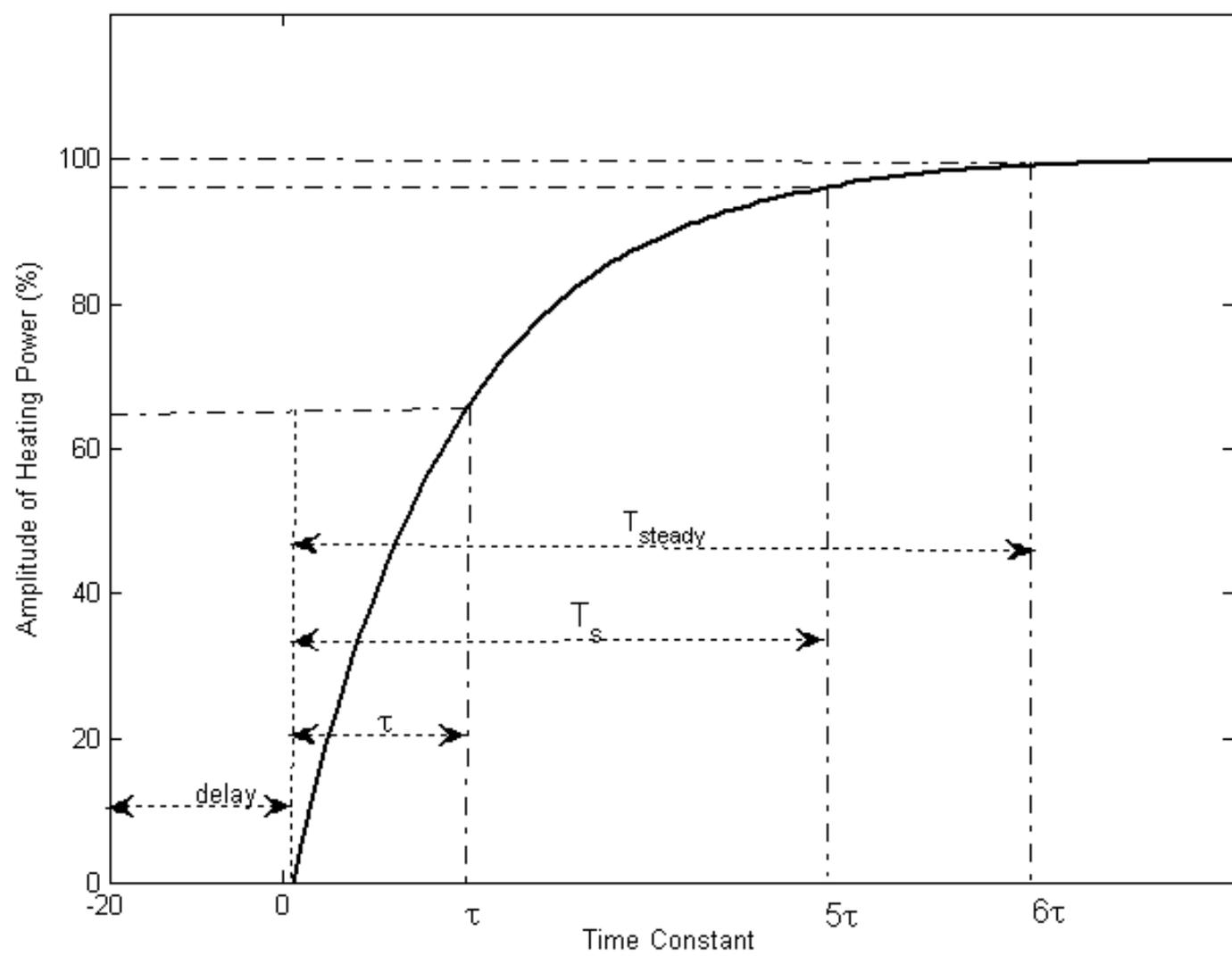


Figure 5

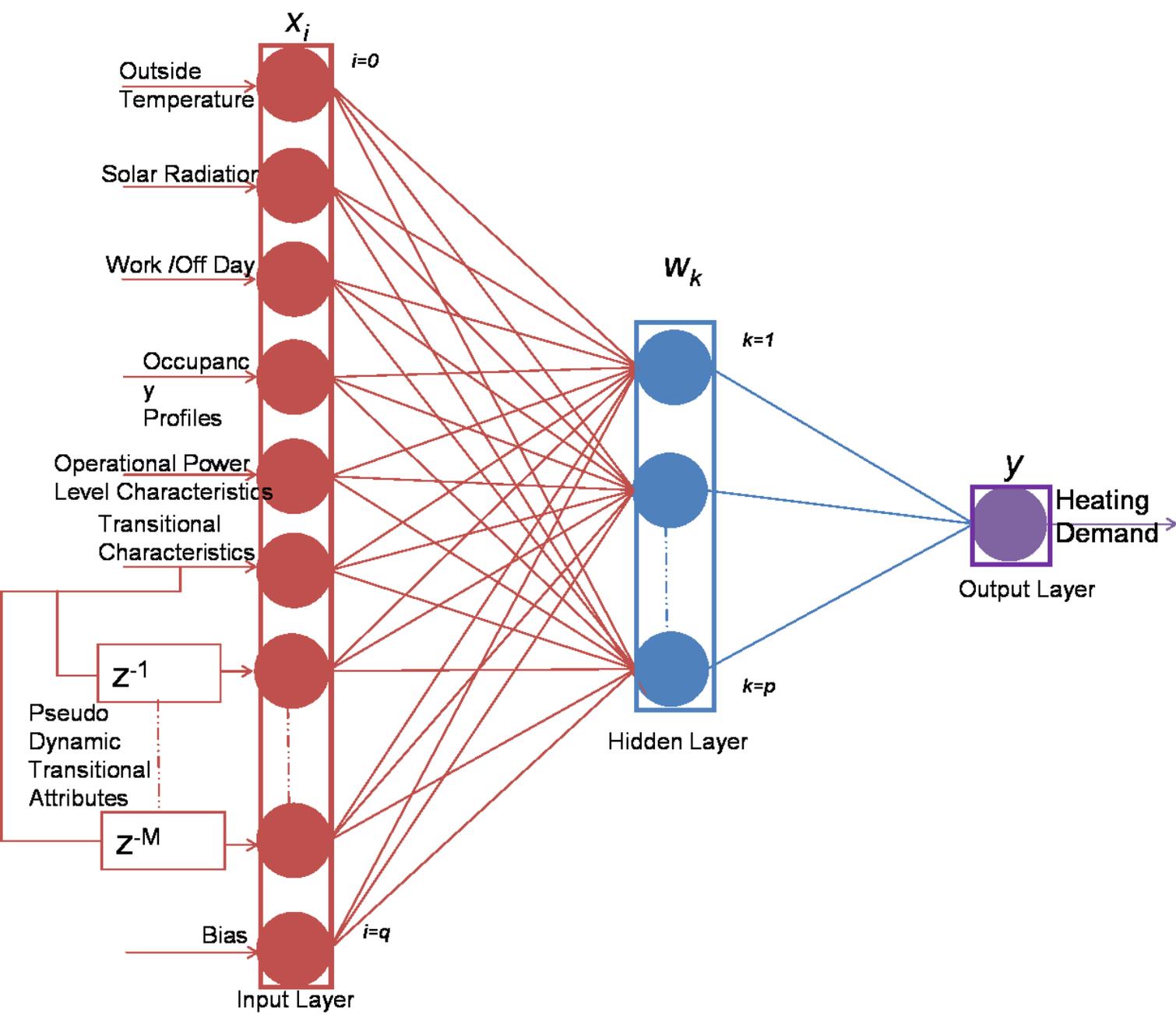


Figure 6

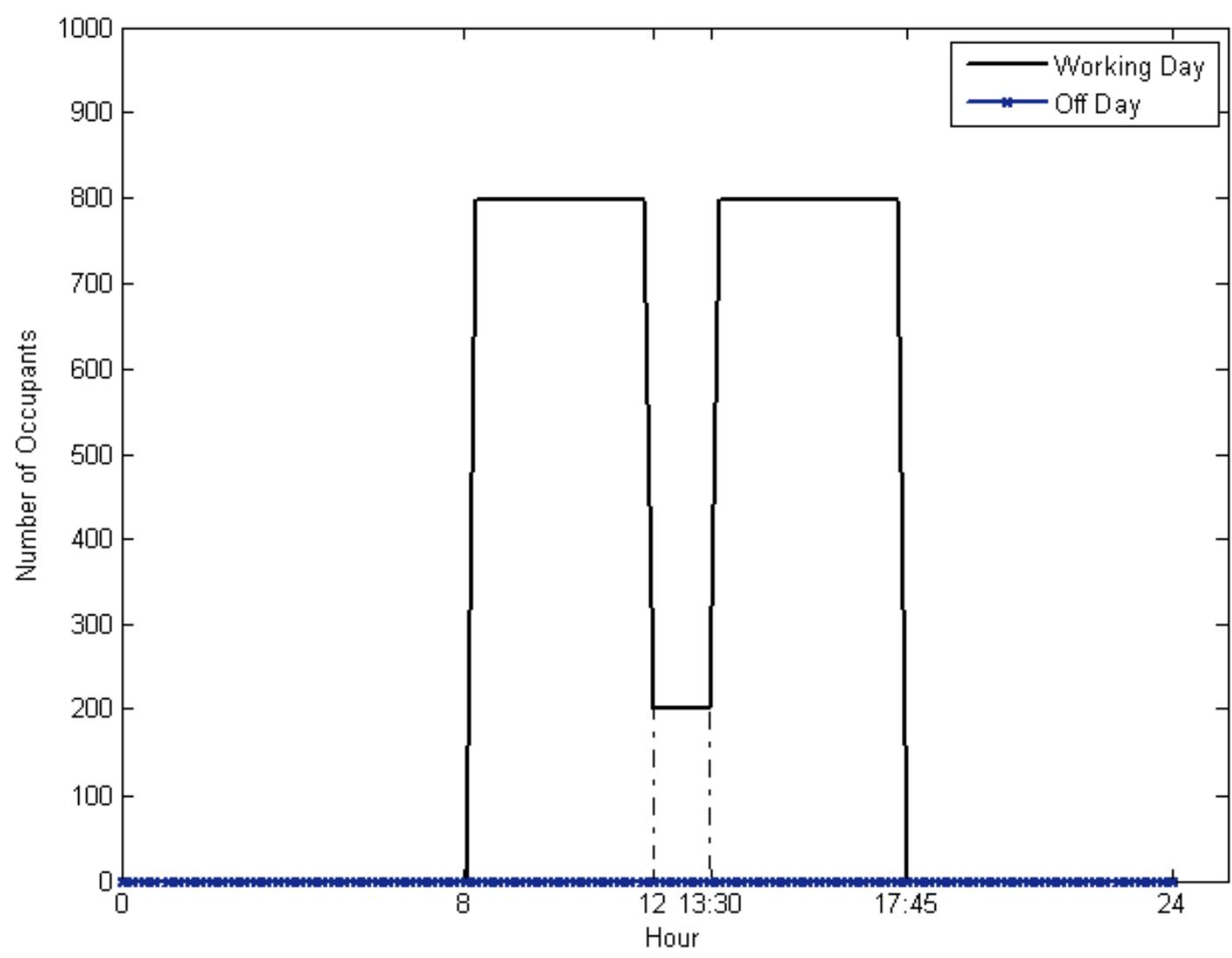


Figure 7

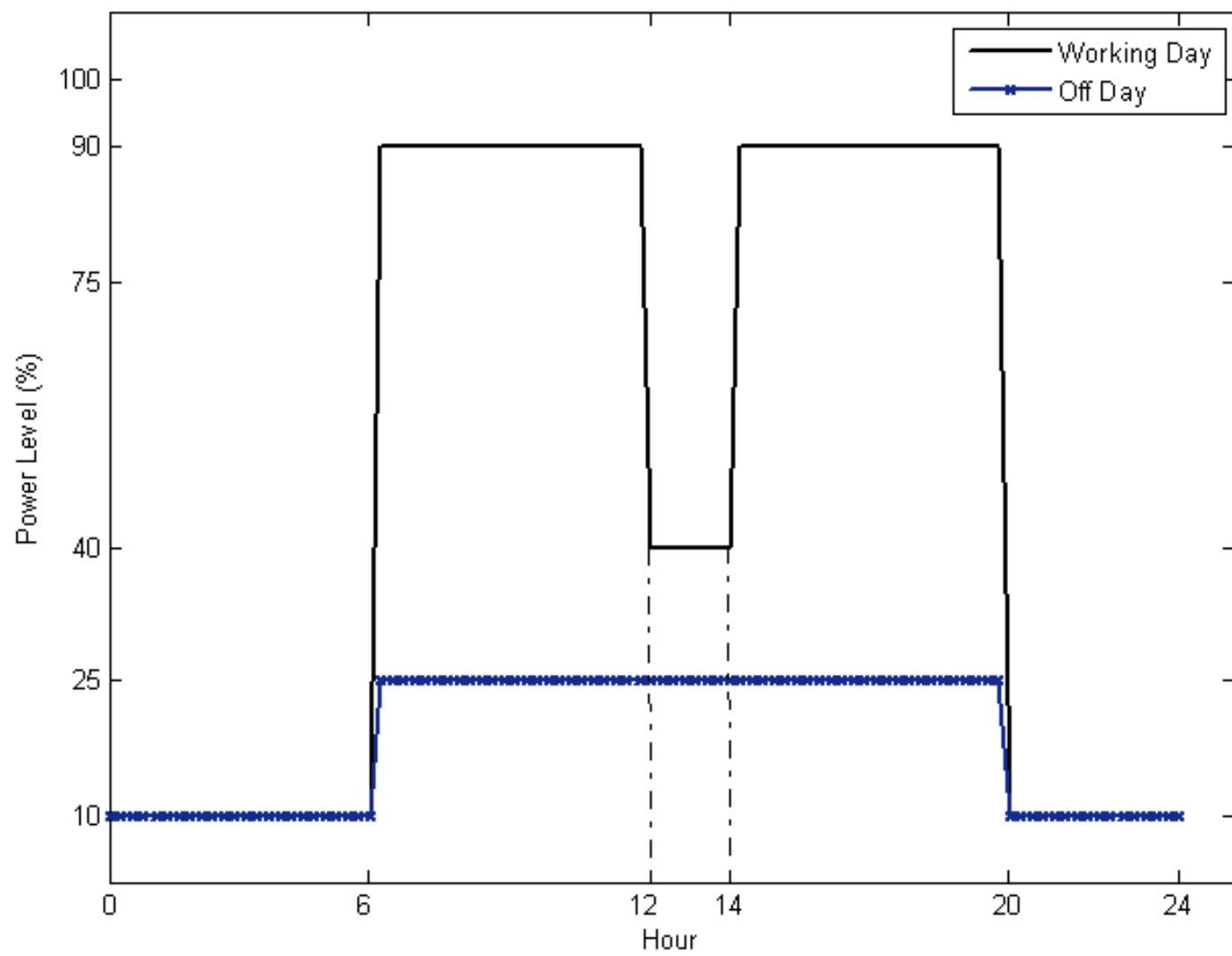


Figure 8

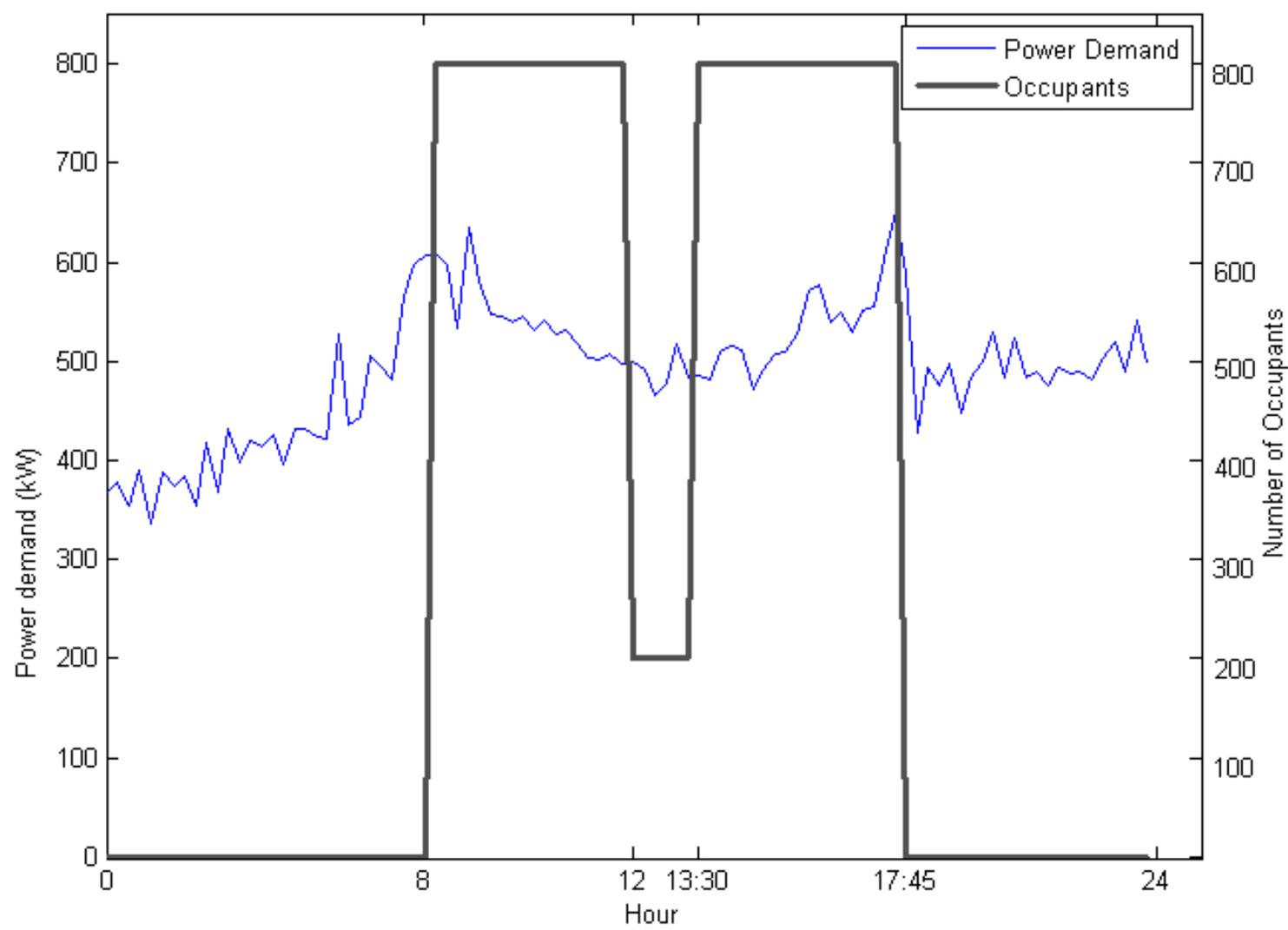


Figure 9

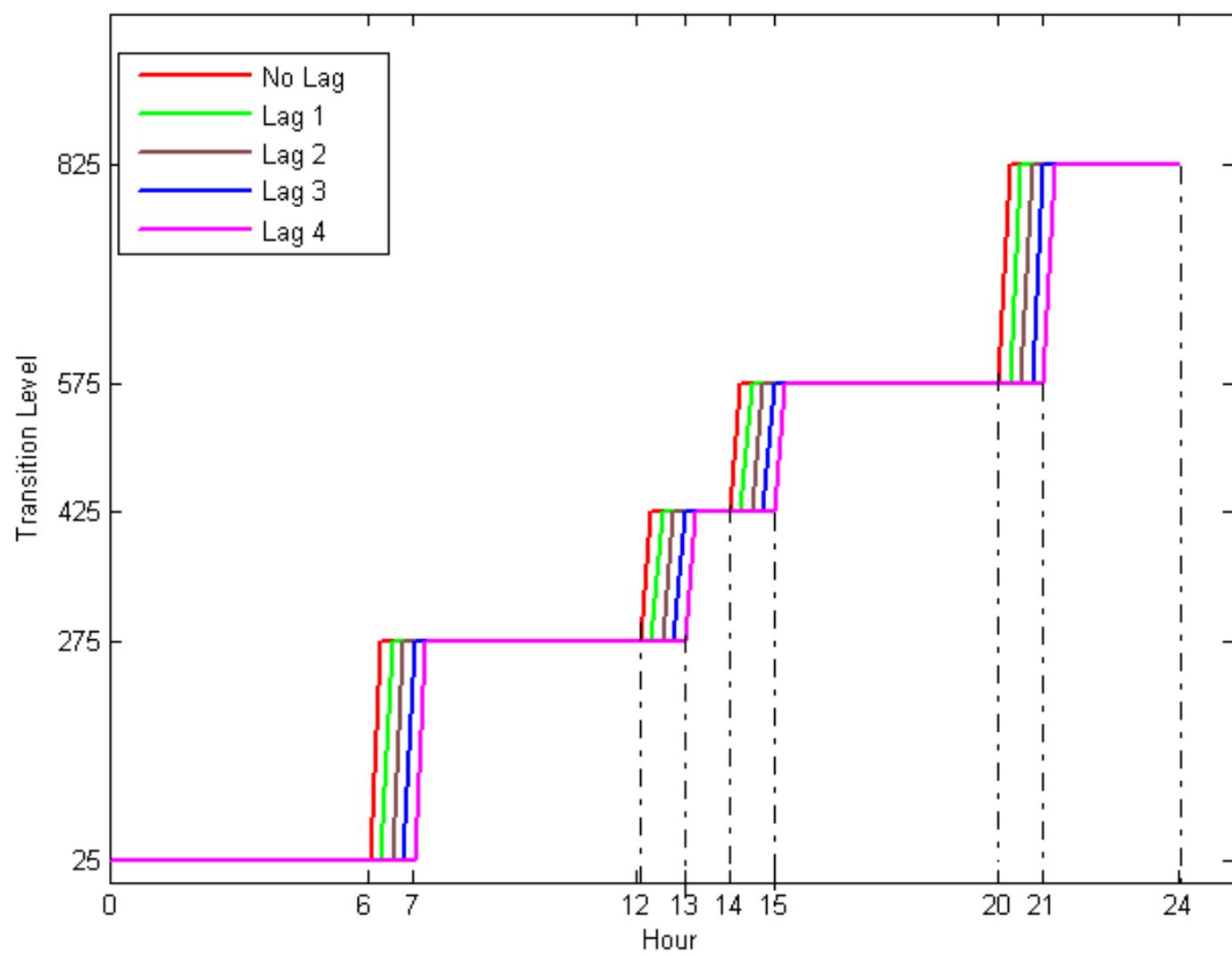


Figure 10

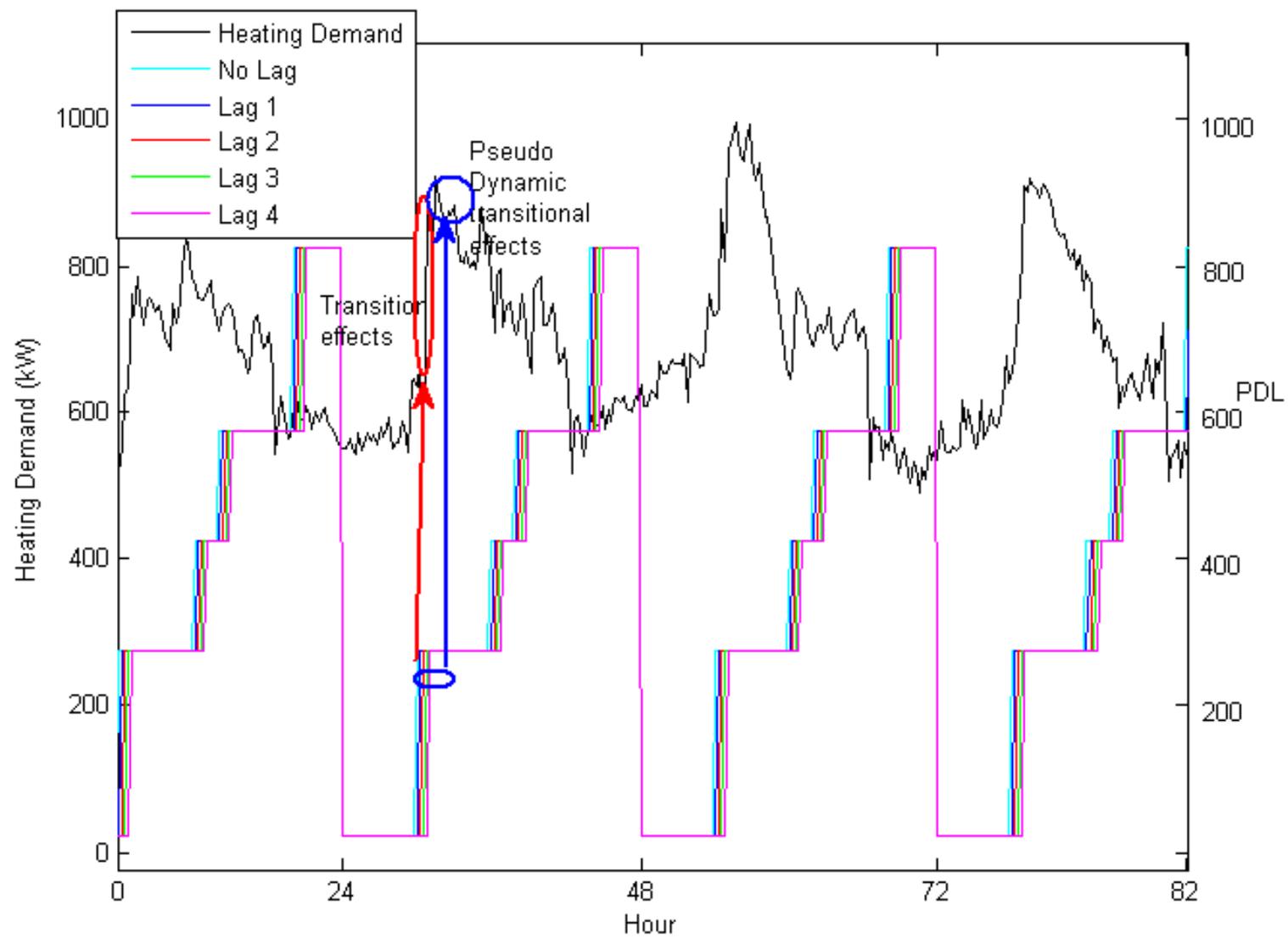


Figure 11

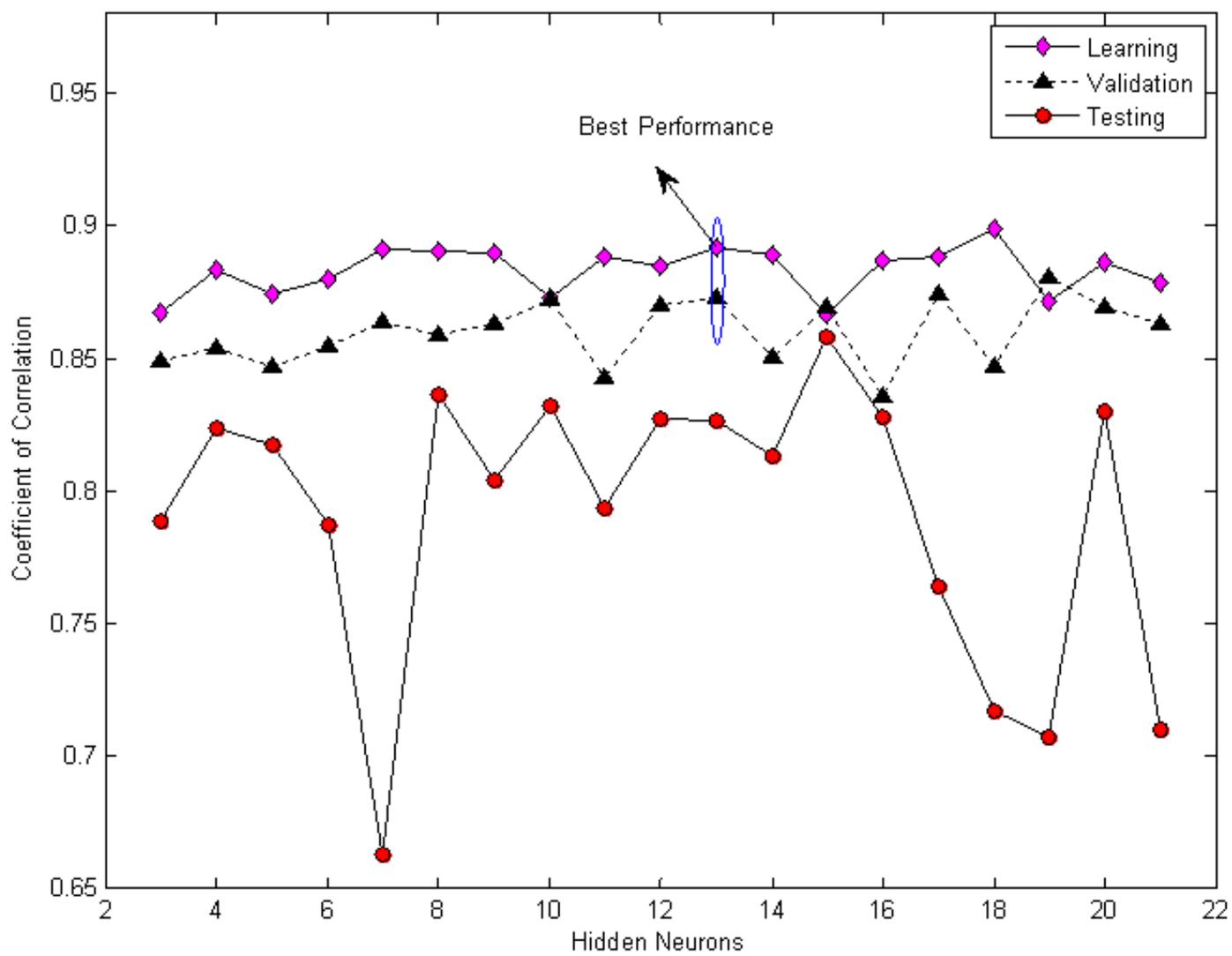


Figure 12

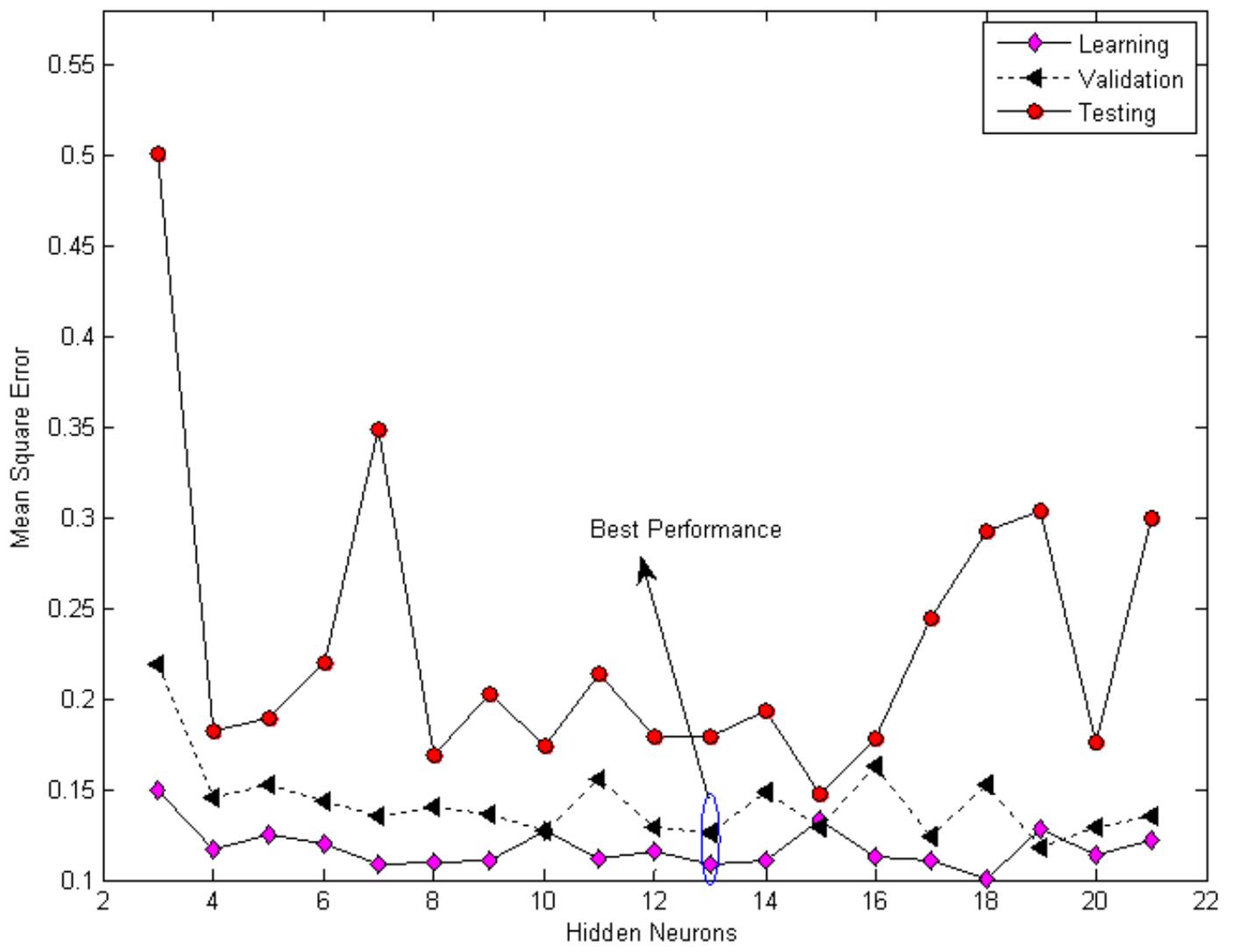


Figure 13

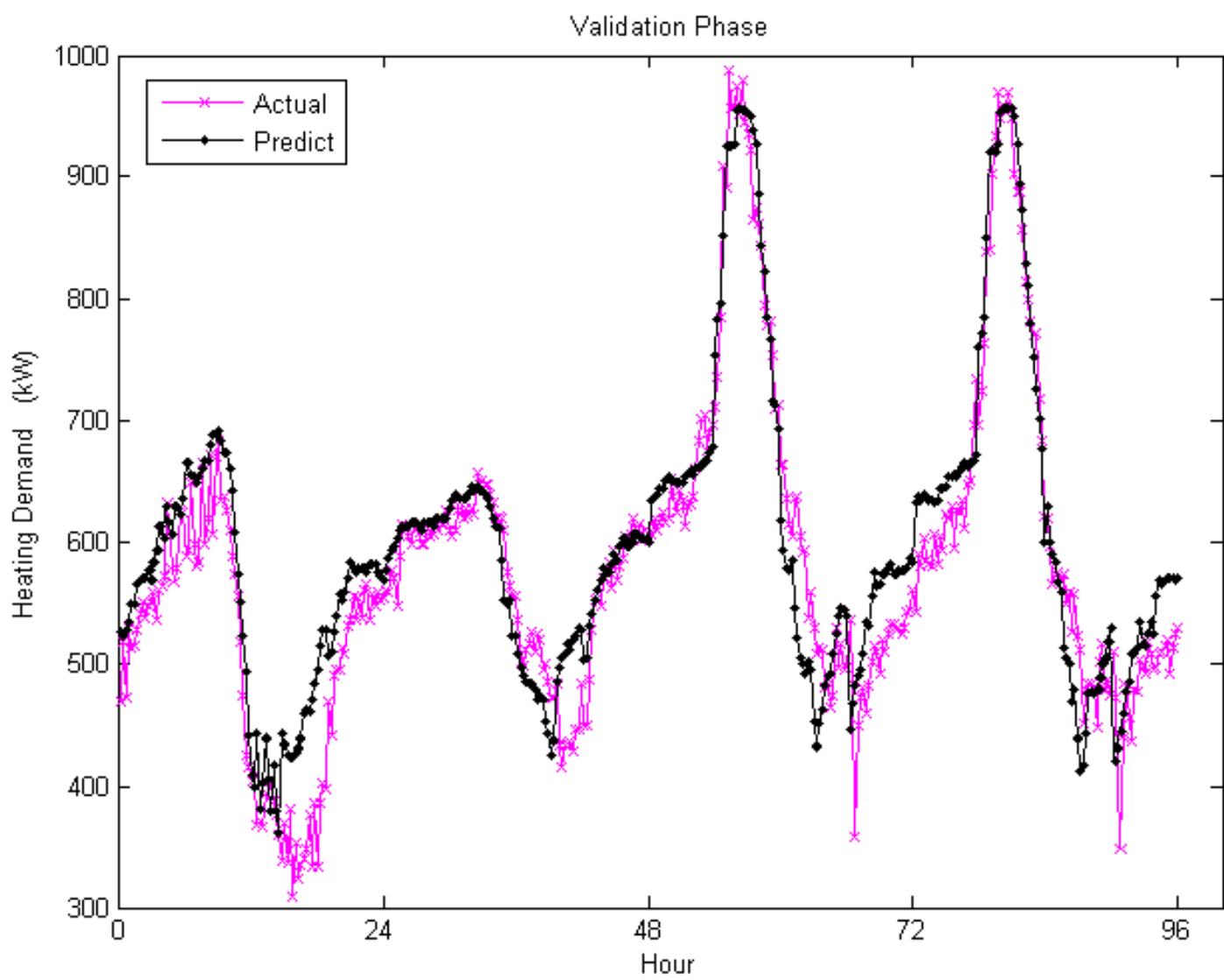
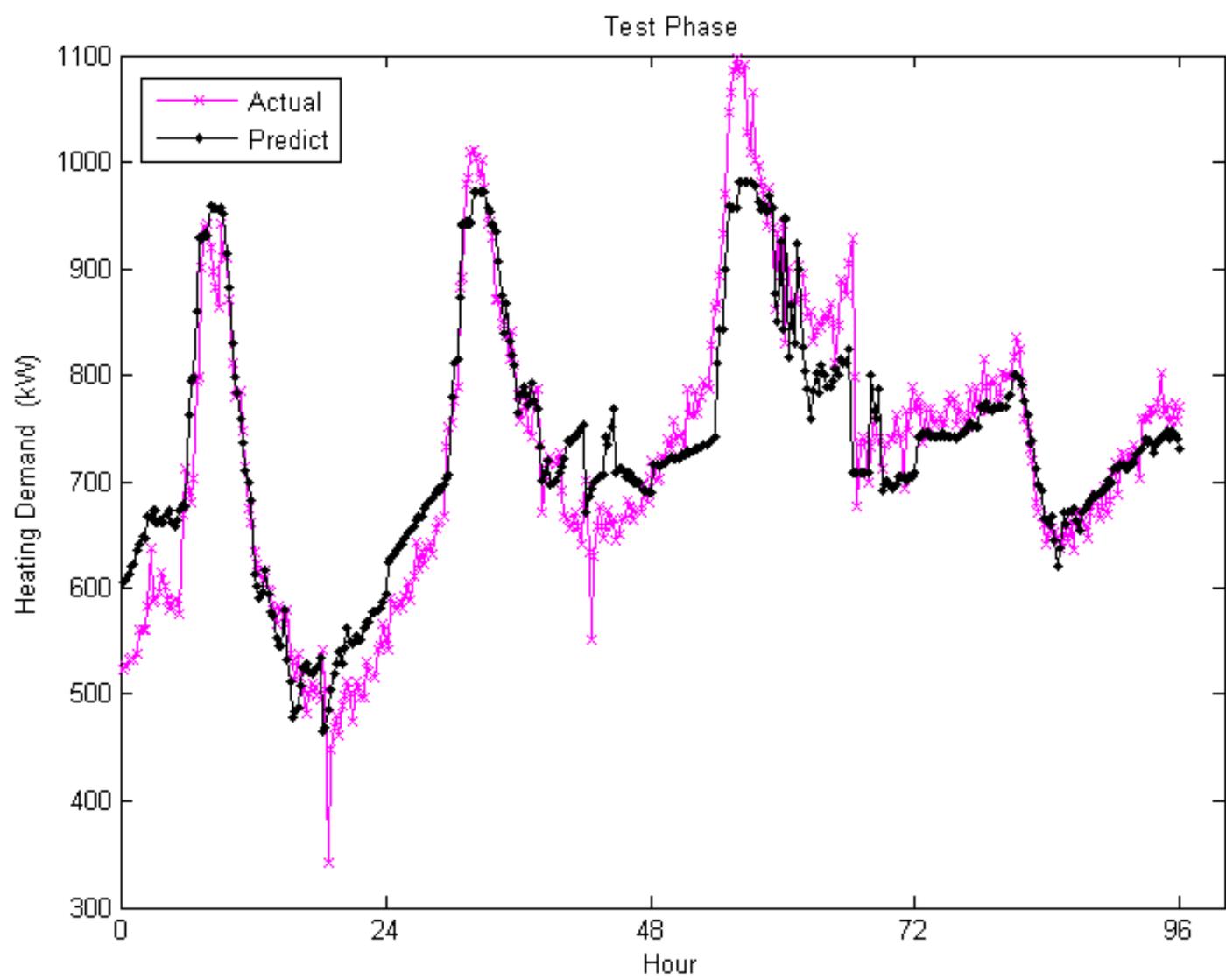


Figure 14



## \*Highlights (for review)

- novel pseudo dynamic transitional model is introduced.
- A large building is considered for application
- The minimum energy consumption error is achieved and is 0.02% for the learning phase and is 2.39%
- orthogonal array design is applied to the pseudo dynamic model (the schedule of occupancy profiles and operational heating power level characteristics)
- application for energy operator to manage the heating load for the dynamic control of the heat production system