A Predictive Approach Based on Neural Network Models for Building Automation Systems

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Abstract. In this paper we address the problem of developing a control strategy to reduce the building energy consumption and reach indoor comfort levels. For this multiple and conflicting objectives optimisation we develop an approach based on stochastic feed-forward neural network models with ARIMA model predictions considered as input variables for networks. Studying real data from a sensorised office located in Rovereto (Italy) we develop the approach and achieve results exhibiting the very good performance of this predictive procedure.

Keywords: Feed-forward neural networks, Prediction, Time Series models, Building Automation System (BAS), Energy Efficiency.

1 Introduction

Energy consumption and carbon footprint are most fundamental issues that our economies and societies are currently addressing to assure a sustainable development. Buildings in particular, both residential and commercial, are responsible for more than 40% of the energy consumption, and this level will rapidly increase if drastic strategies will not be adopted. A critical target of recent EU policies is to transform existing buildings into nearly zero-energy consumption by 2020. In the renovation of existing buildings, an important role is played by building automation systems (BAS) that require new and efficient strategies to work with low energy levels. Control strategies of these systems have to optimise multiple and conflicting objectives, such as low energy consumption and indoor comfort levels. To develop efficient control strategies with these objectives, we have to address the problem of high dimensionality of the system: a very large set of parameters (dimensions) and a complex interacting network are known to affect the dynamical behaviour of the system and have to be involved in any strategy formulation. In current literature, two main approaches are proposed for modelling BAS energy consumption [1]. The former is based on the study of

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the physical system and it is formulated with differential equation sets which describe thermodynamic aspects and features of the environment [2,3]. The latter consists of models (linear and non-linear) which represent the stochastic processes underlying by observed time series with the aim of predicting accurate future dynamics to incorporate in the control strategy [4,5].

Energy observed time series are usually collected by building automation systems and modelled considering both auto-regression (AR) and moving average (MA) components [6,7]. For non-stationary time series, ARIMA models are frequently considered [6], and when exogenous variables are introduced also the ARMAX class of models is derived [8]. Non-linearity in observed dynamics is commonly modelled with artificial neural networks (ANN) as in [9,10]. Interesting are the studies on comfort management with feed-forward neural networks [11] and on predicting lighting and heating systems with radial basis function neural networks [11] or recurrent networks [12]. Other valuable modelling strategies are based on evolutionary neural networks [13] and fuzzy networks, which combine the advantages of both neural networks and fuzzy logic mostly for blur data [14].

In this paper we develop an approach based on stochastic feed-forward neural networks to provide accurate predictions for three building automation system response variables, studying sets of real data recorded in a sensorised office. The system response variables are: energy consumption, indoor thermal comfort and indoor lighting comfort. To develop an optimal control strategy we first derive a selected set of explanatory variables using different statistical variable selection procedures. We then construct ARIMA predictions on these variables to achieve a data set which includes both observed data and univariate predictions. On this composite data set we further construct neural network models and derive accurate predictions for the three system response variables. The research is developed on data collected in a sensorised office located in Rovereto (Italy). The paper is organized as follows: in Section 2 we present the predictive approach by describing the variable selection procedure adopted to reduce the dimensionality of the problem and the construction of the neural network models to derive accurate predictions. In Section 3 we present the case study and the particular modelling strategy that we adopt. In Section 4 we present the results and we evaluate the accuracy of the achieved predictions and the global performance of the approach.

2 The Predictive Approach

Given a set of time series with N observations and denoting by $x_{1,t}, \ldots, x_{p,t}$ the informative variables at time t, $t = 1, \ldots, N$, and by $y_{j,t}$ the j-th system response variable at time t, we develop a general approach to predict system responses for energy efficient buildings by means of stochastic neural networks based on ARIMA model predictions. This approach involves several statistical procedures that are merged together to enhance the predictive performance of neural network models. In particular, we derive the predicted values $\hat{y}_{j,t+\tau}$, $\tau = 1, \ldots, \mathrm{T}$, for each response variable according to the procedure represented in Fig. 1.

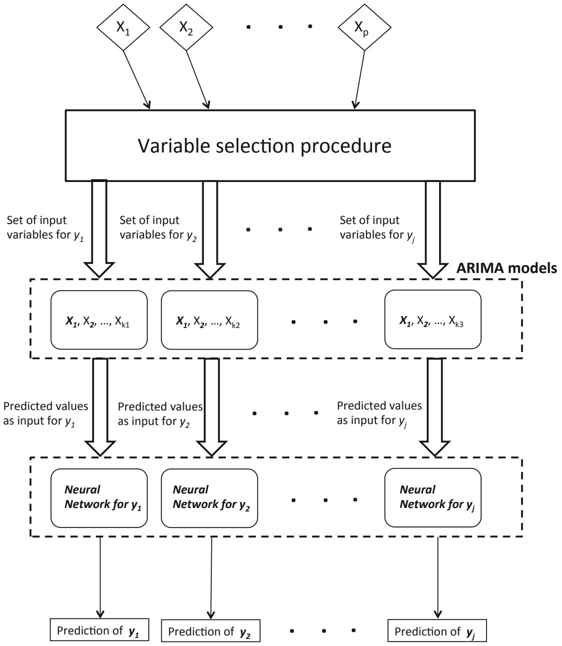


Fig. 1. The general structure of the predictive approach

2.1 Variable Selection Procedure

Addressing the problem of deriving a design for energy efficient buildings, a large set of variables has to be considered and modelled. Some variables represent the endogenous characteristics of a particular state of the system and they are recorded at fixed time intervals. In estimating statistical models to predict the dynamical behaviour of BAS responses, this large set of state variables can be in a *sparse* space where some variables affect more than others the system response. To select just the most informative variables from the very large and frequently noisy set initially collected, we adopt variable selection procedures, combining three different approaches:

- the physical mathematical formulation of each response variable;
- the Spearman correlation index;
- the non-linear variable selection approach based on Random Forests.

Each system response variable is generally described by a physical mathematical formulation based on a set of endogenous variables representing the state of the system [2,3]. Developing our predictive procedure, we decide to select *a priori* all the state variables which are involved in the physical formulation of the system response. Then we identify all the variables that are linearly related with the response by computing the Spearman correlation coefficient ρ [15]. We select those variables that show a significant linear correlation with the response variable achieving $|\rho| > 0.5$.

To identify the informative variables with a non-linear relationship with the system response, we develop a selection procedure based on Random Forest approach. Random Forests have been introduced by [16] and they can be used to rank the importance of a set of variables in a non linear regression analysis. The principle of Random Forests is to combine many regression trees [17] built using bootstrap training samples and randomly choosing at each node of the tree a subset of state variables; successively a prediction performance is computed. Variables that largely influence the prediction error of the regression trees are considered the most influential for the system response: we select the state variables whose normalised prediction error is larger than 0.5 [18].

2.2 The Predictive Neural Network Based on ARIMA

The second phase involves the construction of ARIMA models for those variables selected by the procedure described in Sect. 2.1 and the prediction of each univariate time series $\hat{x}_{i,t+\tau}$, with $i = 1, \ldots, p$ and $\tau = 1, \ldots, \mathrm{T}$.

For each of these variables, an ARIMA model is estimated according to the procedure described in [19], that returns the best model with the lowest AIC value. Each ARIMA model is then used to predict the univariate time series for the following τ observations with $\tau = 1, \ldots, \mathrm{T}$. In the third phase of the procedure we build a class of sigmoidal feed-forward neural network models, one for each system response variable. The sigmoidal neural networks use $x_{i,t}$ and the ARIMA time series predictions, $\hat{x}_{i,t+\tau}$, as input variables to predict the system responses $\hat{y}_{j,t+\tau}$, $\tau = 1, \ldots, \mathrm{T}$. The network topology involves one hidden layer with a number of nodes changing in a specific finite interval, a sigmoidal activation function between the input and the hidden layer and a linear activation function between the hidden and the output layer [20]. All the networks are trained by means of back-error propagation algorithm [21].

To identify which neural network topology can be used to predict each system response, we adopt a bootstrap procedure with B resamples [22]. At each b^{th} run, with $b = 1, \ldots, B$, we select a set of n_b time series observations of the input variables (with $n_b < N$) and we predict $\hat{x}_{i,n_b+\tau}$ observations with the ARIMA models estimated on the n_b observations. We then estimate all the neural networks, whose number of nodes in the hidden layer changes in the defined interval, and we evaluate their prediction error for the future unknown T values of the response. Therefore, at each b^{th} run of the bootstrap procedure we compute a predictive error for each of the chosen topology. We iterate the procedure for B resamples and we identify the topology which minimises simultaneously the Bootstrap Mean Absolute Error (BMAE), as presented in Eq. 1, and its standard deviation.

Once the topology of the network has been identified with the bootstrap procedure, we then proceed to estimate its parameters (weights). We generate a set of different random weights to initialise the network and we train all the networks on the $N - \mathrm{T}$ observed data by means of back-error propagation. Networks are tested for their predictive performance on the remaining T values. The final network is the one which minimises the Mean Absolute Percentage Error (MAPE) as in Eq. 2.

$$BMAE = \frac{1}{\mathrm{T}B} \sum_{b=1}^{B} \sum_{\tau=1}^{\mathrm{T}} |\hat{y}_{n_b+\tau,b} - y_{n_b+\tau,b}| \tag{1}$$

$$MAPE = \frac{1}{\mathrm{T}} \sum_{\tau=1}^{\mathrm{T}} \left| \frac{\hat{y}_{N-\mathrm{T}+\tau} - y_{N-\mathrm{T}+\tau}}{y_{N-\mathrm{T}+\tau}} \right| \tag{2}$$

3 Predicting Building Automation Systems

We construct and test our approach in a real case study addressing a sensorised office located in Rovereto (Italy). In this office, a set of installed sensors are used to record the most relevant **state variables** that affect the energy consumption and the levels of comfort for the office users. In particular, we consider:

- *indoor state variables*: internal temperature (x_1), humidity (x_2), air velocity (x_3), central mean radiant temperature (x_4), west luminosity (x_5), east luminosity (x_6), CO2 concentration (x_7), occupancy (x_8), window sensor (x_9), door sensor (x_{10}), corridor temperature (x_{11}) and fan coil thermal power (x_{12});
- *outside state variables*: outside temperature (x_{13}), outside illuminance (x_{14}), outside radiation (x_{15}) and outside humidity (x_{16}).

A set of **controllable variables** are identified and codified: the power of the fan coil (f_c), the position of the blinder (b) and two dimmable lights (d_1 and d_2).

As **building automation system responses** we measure the total electric power (y_1) - which includes thermal and electric consumptions - and two comfort indices for inhabitants: the Predictive Mean Vote (PMV, y_2) and the Daylight Glare Index (DGI, y_3)[23][24]. PMV measures the level of satisfaction of office users with respect to the thermal environment and it is mostly influenced by temperature, humidity, air velocity and central mean radiant temperature observed in the room. DGI expresses discomfort glare due to the lighting system and depends on luminosity inside the room and electromagnetic radiation given off by the sun.

4 System Response Predictions

We develop the procedure presented in Sec. 2 to achieve the best sigmoidal feed-forward neural network models for predicting the three response variables of the building automation system. Each response variable - Total electric Power (y_1), PMV (y_2) and DGI (y_3) - is predicted by a different neural network topology.

According to the structure presented in Sec. 2, we identify the set of relevant variables for the prediction of each response variable. For Total Electric Power (y_1) we select the following relevant variables: Internal Temperature, x_1; Humidity, x_2; Central mean radiant Temp, x_4; CO_2, x_7; Corridor temperature, x_{11}; Fan Coil thermal power, x_{12}. For PMV (y_2) we select the variables: Internal Temperature, x_1; Humidity, x_2; Central mean radiant Temp, x_4; Corridor temperature, x_{11}. At last, for the third response variable DGI (y_3) we identify the following relevant variables: Humidity, x_2; West luminosity, x_5; East luminosity, x_6; Fan Coil thermal power, x_{12} and Outside Radiation, x_{15}. For each variable, the specific ARIMA model is estimated and used to achieve predicted values $\hat{x}_{i,t+\tau}$, $\tau = 1, \ldots, T$.

We then proceed in the construction of the general approach by selecting a sigmoidal feed-forward neural network with one hidden layer, whose number of nodes ranges from 2 to 20, as described in Sec. 2.2. We select the topology by means of a bootstrap procedure, that has been run for $B = 30$, where each resample uses $n_B = 5000$ time series observations to train the neural network model and the successive T = 72 (6 hours) time series observations to test and validate the results of the predictions. After having identified the topology, we estimate the weights associated to each neural network model, adopting the complete dataset of $N = 29362$ except for the last T = 72 observations which are used as test set. With this general approach, the best model for estimating the Total Electric Power (y_1) involves 12 neurons in the hidden layer and the predicted values $\hat{y}_1(t)$ can be described as a function of the following variables:

$$\begin{aligned}\hat{y_1}(t) = f(&d_1(t), d_2(t), b(t), fc(t), \hat{x_1}(t), \hat{x_2}(t), \hat{x_4}(t), \hat{x_7}(t), \hat{x_{11}}(t), \hat{x_{12}}(t),\\ &\hat{y_2}(t), \hat{y_3}(t), y_1(t-1)).\end{aligned}$$

In this expression, d_1 and d_2 are dimmable lights levels, b is the position of the blinder, fc is the fan coil level and the others represents the selected input variables, predicted by ARIMA models. The response variable itself has been used in the model with a temporal one-lag delay to provide auro-regressive information (as suggested in [9]) and the predicted values of $y_2(t)$ and $y_3(t)$ are also introduced in the model.

With the same procedure, we identify the best topology for PMV, y_2, which is characterised by 11 neurons in the hidden layer and takes the following form:

$$\hat{y_2}(t) = f(d_1(t), d_2(t), b(t), fc(t), \hat{x_1}(t), \hat{x_2}(t), \hat{x_4}(t), \hat{x_{11}}(t), y_2(t-1)),$$

Similarly we identify the best topology for DGI, y_3. The final model has 13 neurons in the hidden layer and takes the following form:

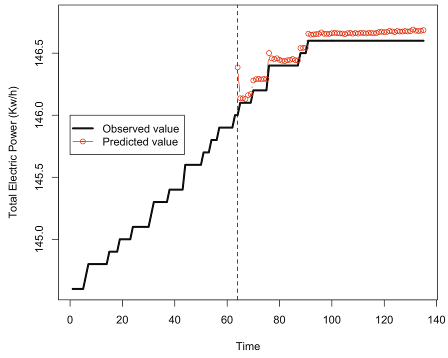
$$\hat{y_3}(t) = f(d_1(t), d_2(t), b(t), fc(t), \hat{x_2}(t), \hat{x_5}(t), \hat{x_6}(t), \hat{x_{12}}(t), \hat{x_{15}}(t), y_3(t-1))$$

To be confident about the behaviour of the estimated neural network models, we evaluate a class of radial basis neural networks and a class of recurrent Elman networks to develop a comparison among different approaches. In the radial basis neural network models we adopt the same strategy to evaluate the best predictive models: a three layer topology is created and a number of neurons from 2 to 20 in the hidden layer is tested. The bootstrap procedure is then run to obtain the BMAE value for each of the topology on the remaining T = 72 observations. In addition, we build a recurrent neural network topology and derive the Elman network architecture by adding a context layer (with the same number of neurons identified for the sigmoidal feed-forward neural networks) to a standard three layered feed-forward network and train them by means of back propagation. We compare these network models in their prediction accuracy on a test set composed of the remaining T = 72 observations (6 hours). The results, as described in Tab. 1, show that sigmoidal feed-forward neural networks are the models that better predict all the responses [10,25].

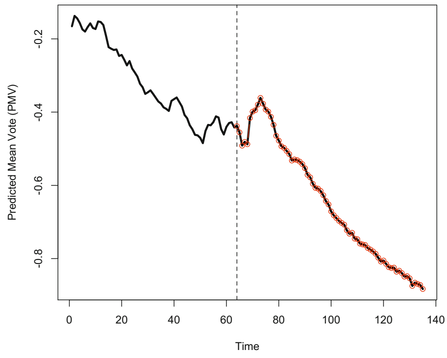
Table 1. Predictive performance metrics of sigmoidal and radial basis neural networks and Elman networks on a 6 hours prediction. In bold the best results obtained for each response. Standard deviations are presented in brackets.

Method	y_1		y_2 (PMV)		y_3 (DGI)	
	MAE	MAPE	MAE	MAPE	MAE	MAPE
Sigmoidal FFN	**0.07** *(0.04)*	$\simeq$ **0** *($\simeq$ 0)*	$\simeq$ **0** *($\simeq$ 0)*	$\simeq$ **0** *($\simeq$ 0)*	$\simeq$ **0** *($\simeq$ 0)*	$\simeq$ **0** *($\simeq$ 0)*
Radial BFN	11.58 *(0.17)*	0.08 *($\simeq$ 0)*	0.51 *(0.20)*	0.79 *(0.20)*	3.35 *(0.23)*	5.10 *(1.28)*
Elman N	0.40 *(0.17)*	$\simeq$ **0** *($\simeq$ 0)*	0.08 *(0.05)*	0.14 *(0.13)*	0.21 *(0.09)*	0.32 *(0.18)*

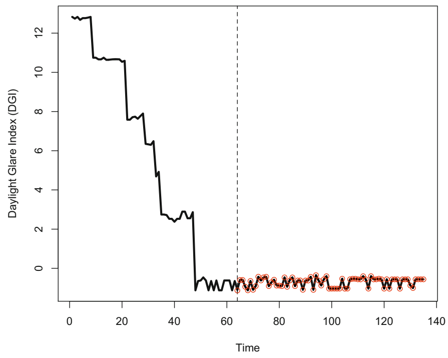
Our approach based on sigmoidal feed-forward neural network gives very good predictions since all the criteria are equal or very close to 0. The sigmoidal feed-forward results exhibit also better performances in comparison with the results obtained using radial basis function network and Elman Network. We present in Fig. 2 the predicted responses in comparison with the actual values recorded by the sensors (Figure 2 presents only the subsample of the last 12 hours in order to make the plots easier to read). We notice that the predicted values for the three responses are very close to the actual real values. In particular we can notice that the prediction of y_2 and y_3 (Figs. *2b* and *2c*) perfectly overlaps the observed values, while only a very small difference can be noticed in Fig. *2a* for the prediction of y_1.



(a) Total eletric power consumption



(b) Predicted Mean Vote



(c) Daylight Glare Index

Fig. 2. Comparison between observed and predicted values for the last 12 recorded hours of the three responses: (a) The Total Electric Power consumption, (b)The Predicted Mean Vote, and (c) The Daylight Glare Index.
Black lines describe the observed values recorded by sensors and red lines describe the predicted values of the sigmoidal feed-forward neural network.

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