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Indoor Air-Temperature Forecast for Energy-Efficient Management in Smart Buildings

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***Abstract*—In the last few years, the reduction of energy consumption and pollution became mandatory. It became also a common goal of many countries. Only in Europe, the building sector is responsible for the total 40% of energy consumption and 36% of CO_2 pollution. Therefore, new control policies based on the forecast of buildings energy behaviors can be developed to reduce energy waste (i.e. policies for Demand Response and Demand Side Management).**
This paper discusses an innovative methodology for smart building indoor air-temperature forecasting. This methodology is based on a Non-linear Autoregressive neural network. This neural network has been trained and validated with a dataset consisting of six years indoor air-temperature values of a building demonstrator. In detail, we have studied three characterizing rooms and the whole building. Experimental results of energy prediction are presented and discussed.

***Index Terms*—Artificial neural networks, Thermal energy forecasting, BIM, Smart Building, Demand Side Management**

I. Introduction

The international conference on climate changes (COP21) has set the goal of reducing energy consumption and CO_2 emission to contrast the greenhouse pollution and the global warming. In the last years, many countries are providing initiatives as incentives to promote the low-carbon and sustainable technologies, especially in the building sector. In Europe, this sector is responsible of 40% of total energy consumption and 36% of total pollution [1]. It follows that there is a strong need to realize tools capable of modeling, monitoring and controlling the building energy behaviors. Information and Communication Technologies (ICTs) and Machine Learning techniques look as key players, especially in the development of new control policies based on systematic knowledge and prediction of energy behavior.

In this work, we present our methodology for indoor air-temperature forecasting to promote an energy-efficient management of smart buildings. This forecast is obtained by exploiting a Non-linear Autoregressive neural network. For this purpose, we designed, trained and validated this neural network with a dataset consisting of six years of indoor air-temperature values. Due to a lack of data, the dataset was realized using EnergyPlus simulations. As demonstrated in [2], using a *Building Information Model* (BIM) of the building and real weather data, we are able to create a consistent artificial dataset. The neural network is a Multilayer Perceptron exploiting a high number of regressors to predict the temperatures in 15 minutes time steps, studying the trend of air-temperatures up to about two hours onwards.

The novelty of our methodology consists of using a neural network able to base its forecasts on a greater number of regressors. Generally, most literature methodologies rely on the single past value. Results of these predictions can foster new control policies and new tools in the energy management of buildings and districts. For example, it allows exploiting the flexibility of electro-thermal devices, that are increasingly used for residential space heating. In this view, building heating systems can be included in Demand/Response [3] and Demand Side Management applications [4] that consider also the ambient comfort [5]. In case of district heating, predicting building energy profiles allows reshaping thermal energy to reduce the peaks [6].

The rest of the paper is organized as follows. Section II reviews literature solution to forecast indoor air-temperature in buildings. Section III introduces the followed methodology to define a neural network to forecast indoor air-temperature in short- and medium-term. Section IV details all the steps performed to initialize, train and validate our neural networks. Section V presents the case study based on a real building. Section VI debates the results on indoor air-temperature forecast. Finally, Section VII discusses concluding remarks.

II. Related Work

In recent years, many works in literature are focused on energy modelling methods for building performance analysis, which represent a key challenge to control and manage energy-efficient Smart Buildings. The common purpose consists of reducing energy consumptions and CO_2 emissions. For example in Europe, buildings are responsible for about 40% of total energy consumption, which represents about 36% of CO_2 emissions.

Different techniques of building performance simulations have been widely studied in literature [7], [8]. Furthermore,

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commercial software tools have been developed. For example, EnergyPlus [9] and TRNSYS [10] represent milestone tools for buildings energy simulations. Although these tools are widely used and provide very detailed results, they have very high computational costs and they need time to perform the simulation (according to the complexity of the model) [2]. Consequently, both tools are less suitable for a Model Predictive Control (MPC) based on thermal control of Smart Buildings. On this view, researchers developed compact thermal modelling systems to reduce both computational costs and simulation time. For example, some systems use classical truncated-balanced realization method [11], [12]. Other solutions, using an electric analogy and representing the thermal model as an RC-network, exploit aggregation-based reduction approach to perform localized reductions to preserve some network properties (i.e. the electrical analogy and some physical common aspects) [13]. Furthermore, ad-hoc reduction methods have been developed to extract linear dynamics of thermal behaviors of buildings from EnergyPlus [14], [15]. More broadly, these compact thermal modelling approaches are methodologies that start from an accurate building model and perform approximation to obtain a compact model via i) model order reduction, ii) model aggregation or ad-hoc dynamics extraction. However, these systems have some limitations: i) they need detailed structure information and equations of thermal systems; ii) often such information is not available or is very difficult to find; iii) the reduction process may introduce a very significant loss of accuracy.

Other solutions propose to build thermal models for VLSI systems. Generally, these methods are based on matrix pencil [16] and subspace identification [17]. The main advantage is the flexibility given by the absence of physical restrictions. They are very accurate during the training phase thanks to the analysis of detailed numerical simulation or measured data (i.e. information sample on the field). However, these solutions cannot deal with the non-linearity of the dynamic thermal system, such as a whole building. A solution is given by machine learning techniques and in particular by neural networks that provide compact and smart thermal models for non-linear dynamic systems. In [18], the authors exploit a fictitious model of a simple building to produce a synthetic dataset with EnergyPlus. Then, this dataset is used for training two Recurrent Neural Networks (RNN), a non-linear state-space RNN and an Elman's RNN, respectively. In this way, they built a very accurate thermal models of a simplified building, achieving also good results in terms of performance and time. However, this methodology is based on a simplified model of a fictitious building and, as pointed out by authors, the error rate increases when the model of the building becomes more complex. This makes their methodology ineffective for studying real building's dynamics.

In this paper, we present a non-linear neural network to forecast indoor air-temperature. With respect to literature solutions, the novelty of our methodology consists on using i) a Multilayer Perceptron-based neural network and ii) a real BIM model of a real demonstrator together with real weather data to recreate a consistent artificial dataset. The proposed solution allows us to reduce significantly the *prediction error* by using a high number of regressors to perform the forecast. Generally, most literature solutions based on neural networks rely on the single past value (i.e. a single regressor) to perform predictions. Thanks to the proposed non-linear neural network, we perform the forecast of indoor air-temperature in a building in short- and medium-term, i.e. from 15 minutes up to next 3 hours.

III. Methodology

Predicting the thermal behavior of a building means working with time series information. One of the most effective methods for prediction, starting from time series information, consists of neural networks [19], such as the Multilayer Perceptron (MLP). This artificial neural network is one of the most widespread and used. Generally, an MLP neural network is composed of units (called nodes or neurons) organized in a layer of inputs, one or more hidden layers and an output layer. It is also a feed-forward and a fully connected (between layers) network. The connections are characterized by adjustable parameters called weights. These refer to the strength of a connection between two nodes. Each neuron computes a function of the sum of the weighted inputs. This function is called *activation function*.

In this work, we use an MLP-network architecture characterized by i) one hidden layer of neurons with hyperbolic tangent activation function and ii) an output layer with a linear activation function. The network is subjected to a training phase that allows determining a mapping from the set of training data to the set of possible weights. In this way, the network can produce prediction, to be compared to the true output.

According to [20] and as widely detailed in [21], the procedure to identify a dynamical system consists of four phases: i) *Experiment*, ii) *Model Structure Selection*, iii) *Model Estimation* and iv) *Model Validation* (see Figure 1).

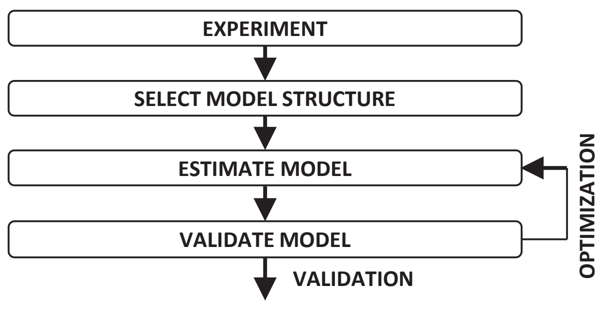


Fig. 1: System identification procedure

The *Experiment* is the problem analysis and the data sampling and collection phase. Once the scope has been identified, a big and relevant amount of data is needed to forecast performances. The data must be divided into two sets: training-set and validation-set. These are used in the neural network training and validation steps. The *Model Structure Selection* phase identifies the correct architecture model and the number of regressors [20]. In time series, the regressors represent previous samplings with respect to the predicted ones [19]. In the *Model Estimation* phase the network is firstly implemented and then trained. The training process produces a *training error*, which represents the network performance index. The *Model Estimation* allows validating the trained network in order to evaluate its capabilities. In time series predictions, the most common validation method consists of analyzing the residuals (i.e. prediction errors) by cross-validating the test set. This analysis provides the *test error*, that is an index considered as a generalization of the error estimation. This index should not be too high compared to training error, if this happens the network could over-fit the training set. This means that the selected model structure contains too many weights. In this case, it is required to return in the *Estimate Model* step in order to change and redefine some structural parameters by optimizing the whole architecture. For this purpose, the superfluous weight must be pruned according to the Optimal Brain Surgeon (OBS), that represents one of the most important optimization strategies [22]. Consequently, once the new weights are given, the network architecture must be re-validated.

IV. NAR NEURAL NETWORK FOR BUILDING THERMAL ENERGY FORECAST

In this work, we aim at forecasting the smart building thermal energy behaviors. For this purpose, we used a dataset of about six years (from 2010 to 2015). It provides realistic artificial indoor air-temperature values, sampled every 15 minutes. In detail, we considered all values in the time period from November to March, which referrers to the operational period of the building heating system in our country. We decided to study the building, as a whole, and three characterizing rooms chosen in relation to building shape and their occupancy during the week (Section V details the requirements that characterize the selected demonstrator environments). For this purpose, we designed and implemented the neural network first, then we trained and validated it, one for each case study. We split the dataset into a training-set (2010-2013) and validation-set (2014-2015). In order to deal with time series data, we adopted the Non-linear Autoregressive neural network (NAR) belonging to the Non-linear Autoregressive Exogenous Model (NARX) family [23]. NARX is considered one of the best tool in time series analysis (used as NAR) because it does not suffer from stability problems. It bases its predictions on i) past values of the series and ii) current and past values of the driving exogenous series, producing an error that represents the error of prediction. This error means that the knowledge of the past terms does not enable the future value of the time series to be predicted exactly.

Once the model has been chosen, we analyzed the number of past signals used as regressors for the prediction. We used *Lipschiz* method for determining the *lag-space* [24]. This methodology allows identifying the orders of Input-Output Models for Non-linear Dynamic System. This study was carried out for each studied environment, then for each neural network. As detailed in [21] and comparing the results obtained, we deduced that the architectures have a good performance with 13 regressors. Then, we chose an initial fully connected network architecture with one hidden layer of 30 hyperbolic tangent units. The weights of the network are then initialized randomly before a training. This choice allows to initialize i) the weights, ii) their decay threshold and iii) the maximum number of iterations. After this phase, we proceed in training the neural network. Training is a minimization technique to compute the best weights for the network. Here, we used the *Levenberg-Marquardt* algorithm, which interpolates between the Gauss-Newton algorithm and the method of gradient descent, using a *trust region* approach [20].

According to the purpose of this study, we chose to use the methodology illustrated in [25] for the network validation. This allows the model systems validation of the outputs, performing a set of tests including autocorrelation function of the residuals and cross-correlation function between controls and residuals. This process produces the test error index as a result. The test error represents an estimation of the generalization error. If the test error ($NSSE$) is greater than the training error, it means that the predicted results are over-fitting the training set. Table I illustrates the obtained results.

TABLE I: NSSE comparison after the first and final validation

Rooms	NSSE after first validation	NSSE after final validation
Classroom West	2.26×10^{-2}	2.01×10^{-2}
Classroom East	1.56×10^{-2}	1.34×10^{-2}
Corridor	1.92×10^{-2}	1.90×10^{-2}
Whole Building	1.29×10^{-2}	1.28×10^{-2}

In our case, the validation process yields these indexes as detailed in the column *NSSE after first validation*. Then, we proceeded to the optimization phase of the network. Our purpose was to remove weights in excess and obtain a smaller training error than the one given during the first validation. In order to do so, we adopted the *Optimal Brain Surgeon* (OBS) strategy, which prunes superfluous weights, as mathematically detailed in [21]. Through the same methodology used in the first validation phase, we proceeded to the final network validation using the new weights. The resulting test error indexes NSSE are illustrated in the column *NSSE after final validation* of Table I. In all cases, the indices are lower than the previous ones. Thus, the prediction error has been further lowered, giving a more precise fo Furthermore, to validate the number of regressors initially found with the Lipschitz methodology, we performed a further evaluation of NSSE after pruning. We repeated our tests with different regressors. Figure 2 shows the resulting NSSE for the four environments. It highlights that NSSE decreases by increasing the number of regressors and the best results, for the four environments, are achieved with 13 regressors.

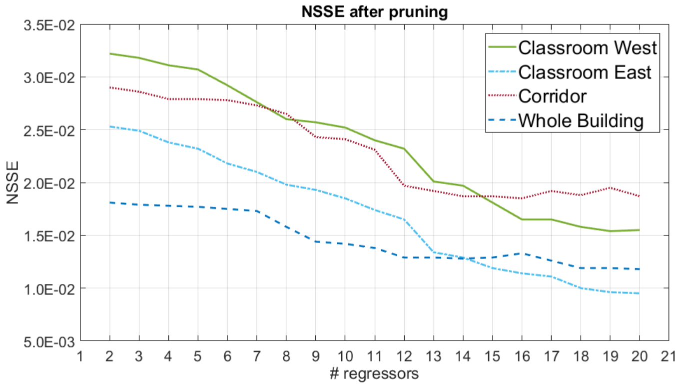


Fig. 2: Evaluation of NSSE after pruning with regard to the number of regressors

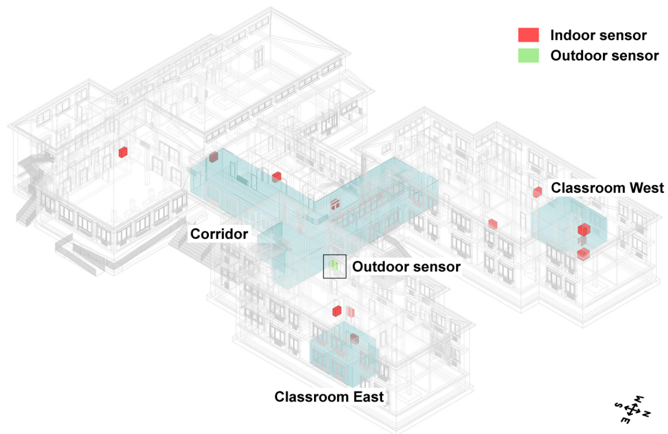


Fig. 3: BIM model of the building and reference rooms.

V. Case Study

The methodology described in Section III and Section IV has been applied on a public building. This building is a primary school of about $14500\ m^2$ spread on two floors and located in north-western Italy. The building is connected to the district heating distribution system and is not equipped with conditioning system. Windows on brick walls facades are double glazed. Both east- and west-oriented facades receive substantial contributions of thermal energy due to solar radiation, which is a natural heat load contribution. By analyzing the structural information of this building (i.e. geometry, materials, thermal and physical properties of building components), we built its BIM model (see Figure 3). According to symmetrical shapes and regular internal distribution, we have selected three relevant rooms: i) a classroom facing west, ii) a classroom facing east and iii) the corridor at the main entrance. Both classrooms are comparable in size, internal characteristics, use and occupants. They differ only in the orientation. The corridor is not characterized by a constant occupancy during working-days. It is significant for this study because it is a very large environment located in a central position of the building with many openings and glazed windows.

In our case study building, we installed Internet-of-Things devices to monitor the air temperature trends. However, the collected data are not enough. Since the neural network needs a large amount of data for both training and validation, we simulated the thermal energy behavior of our building with EnergyPlus. We used the BIM model together with real weather data of the last six years as input to EnergyPlus simulations. Traditionally, these simulations are performed using *Typical Meteorological Year* (TMY) data. However, as demonstrated in [2], performing simulations with EnergyPlus combined with real weather information gives as output indoor air-temperature trends with a low error rate. Based on these indoor air-temperature trends (in the form of time series), we built our consistent artificial dataset. Finally, we used this dataset for training and validating the proposed neural network, as described in Section IV.

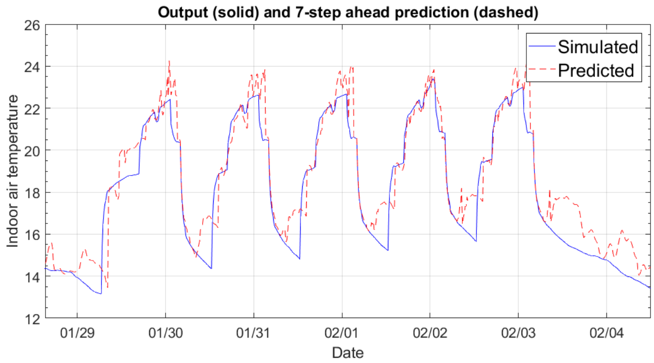
VI. Results of Indoor Air-Temperature Forecast

Our goal is to predict values of indoor air-temperature in the longest time period with the best accuracy. Using the dataset described in Section V, we performed predictions by employing the methodology above-mentioned. This methodology allows to determine the prediction values (that corresponds to the ahead k-step prediction of the system) and compare them to the original output. k represents the sampling time. In our study, a single step corresponds to 15 minutes. We applied the proposed neural network to the three selected rooms and to the whole building (see Section V) and we present the obtained results in this section. Before starting the simulations, we set the prediction function to 13 regressors for each neural network. Then, we perform simulations up to $k = 16$ (i.e. 240 min.). To evaluate the performance of our predictions, we used the following indicators as described in [26]: i) the *Root Mean Square Difference* (RMSD) - the standard deviation of differences between predicted and observed values; ii) the *Mean Absolute Difference* (MAD) - a measure of statistical dispersion obtained by the average absolute difference of two independent values drawn from a probability distribution; iii) the *Mean Bias Difference* (MBD) - the average squares of errors between predicted and original values.

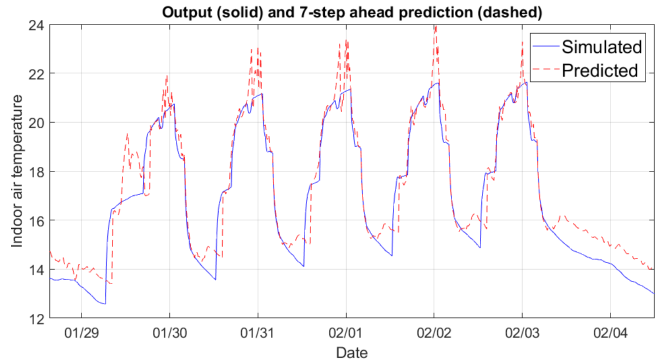
Table II reports the results in terms of performance indicators for the three rooms and the whole building. Values in bold represent the maximum forecast threshold, thus the maximum $k-step$ prediction with good accuracy. These indexes clearly show that the neural network performance worsens by increasing $k-step$. The analysis of the indices shows that making the forecast beyond the three hours ahead is not possible because the error rate would not respect the constraints of indoor thermal comfort. We identified $MAD = 0.750$ as the maximum acceptable threshold. This threshold represents the maximum limit within which indoor temperature changes do not impact on environmental thermal comfort perceived by the occupants [27]. As reported in Table II, *MAD* indicates that the error grows as the prediction step k increases. Also *RMSD* and *MDB* have similar trends. However, in this case study, results for each room and for the whole building must be considered individually. Indeed, results for the whole building highlights

TABLE II: Performance indicators for indoor air-temperature forecast

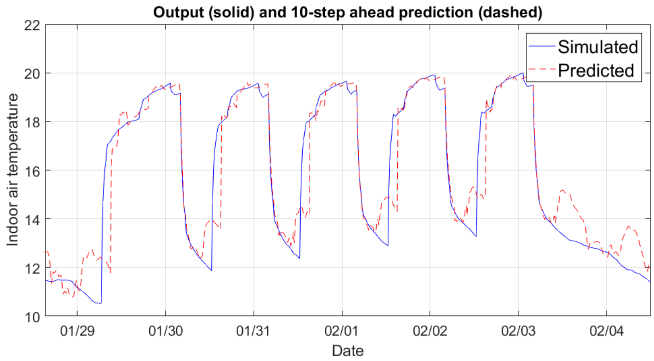
		Rooms											
		Classroom West			Classroom East			Corridor			Whole Building		
Prediction Steps	Time [min]	MAD	MDB	RMSD	MAD	MDB	RMSD	MAD	MDB	RMSD	MAD	MDB	RMSD
k=1	15	0.381	-0.003	0.704	0.348	0.001	0.635	0.298	-0.001	0.733	0.208	-0.001	0.471
k=2	30	0.371	0.010	0.655	0.342	0.021	0.607	0.289	0.007	0.673	0.202	0.009	0.429
k=3	45	0.404	0.044	0.609	0.372	0.055	0.580	0.304	0.025	0.590	0.213	0.024	0.377
k=4	60	0.489	0.093	0.683	0.445	0.103	0.635	0.360	0.050	0.625	0.257	0.036	0.419
k=5	75	0.589	0.144	0.800	0.533	0.158	0.731	0.431	0.076	0.715	0.305	0.044	0.480
k=6	90	0.689	0.188	0.934	0.630	0.215	0.884	0.501	0.095	0.820	0.356	0.050	0.550
k=7	105	**0.749**	**0.229**	**1.080**	**0.741**	**2.282**	**0.977**	0.567	0.104	0.918	0.415	0.063	0.620
k=8	120	0.904	0.255	1.215	0.869	0.363	1.129	0.628	0.103	1.014	0.479	0.080	0.690
k=9	135	1.001	0.270	1.340	1.003	0.455	1.292	0.684	0.093	1.107	0.539	0.096	0.765
k=10	150	1.092	0.271	1.458	1.134	0.550	1.458	**0.740**	**0.080**	**1.204**	0.597	0.108	0.836
k=11	165	1.177	0.264	1.570	1.266	0.649	1.627	0.794	0.065	1.299	0.652	0.119	0.900
k=12	180	1.249	0.255	1.674	1.398	0.758	1.802	0.835	0.056	1.386	0.698	0.133	0.954
k=13	195	1.311	0.246	1.772	1.541	0.877	1.991	0.869	0.048	1.452	**0.740**	**0.148**	**0.998**
k=14	210	1.382	0.238	1.865	1.692	1.005	2.193	0.896	0.040	1.498	0.774	0.160	1.040
k=15	225	1.439	0.233	1.961	1.858	1.137	2.407	0.943	0.038	1.562	0.821	0.170	1.103
k=16	240	1.512	0.223	2.050	2.042	1.279	2.638	0.999	0.035	1.628	0.873	0.181	1.184



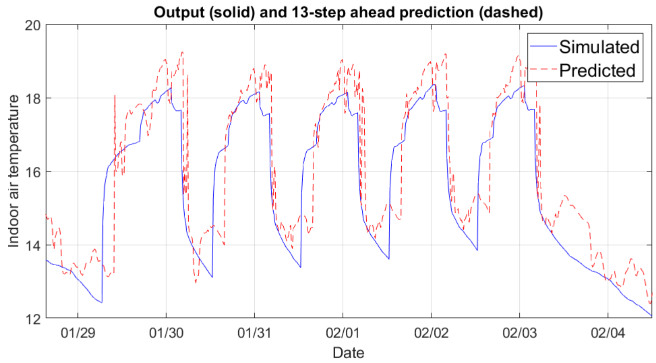
(a) Classroom West: Prediction for $k = 7$ (105 min.)



(b) Classroom East: Prediction for $k = 7$ (105 min.)



(c) Corridor: Prediction for $k = 10$ (150 min.)



(d) Whole Building: Prediction for $k = 13$ (195 min.)

Fig. 4: Indoor air-temperature predictions with maximum allowed k-step for each room (February 2013)

that predictions can be done up to next 195 min. ($k = 13$) with $MAD = 0.740$, $MDB = 0.148$ and $RMSD = 0.998$. This is due to the original dataset used to train the neural network for the whole building. This dataset consists of a trend of indoor air-temperature over the time (one sample every 15 min.). This trend is given by averaging the single air-temperature values of each room in the building (i.e. 110 rooms). Thus, the resulting trend is much smoother with respect to the trends of the three selected rooms. This makes easier the training of the neural network. Whilst, the different exposures and uses of the three rooms give non-homogeneous temperature trends. This affects the forecasts that can be done up to next 105 min. ($k = 7$), for both Classroom West and Classroom Est, and up to next 150 min. ($k = 10$), for the Corridor.

Figure 4 shows the comparison among indoor air-temperature results given by our neural networks (dashed lines) and the realistic artificial values give by EnergyPlus (continues line) for each room and different $k - step$. These trends refer to the first week of February 2013. As can be seen in the four plots, trends of our results follow the realistic behavior of indoor air-temperature with a good accuracy.

In our view, the obtained results are very satisfactory and allow us to design new control policies with different granularities that take advantage of air-temperature forecasts to foster services like Demand Response and Demand Side Management. For example, in a building scenario, such policies can control every single room exploiting predictions up to about next two hours. Whilst, in a district scenario, policies to dispatch thermal energy through heating distribution systems needs information about the building as a whole. Thus, they can take advantage of forecasts up to about next three hours. In both scenarios, the comfort of building inhabitants is ensured.

VII. Conclusions

In this paper, we presented a methodology to forecast indoor air-temperature in Smart Buildings. We discussed the characterizing results of the neural networks forecast, introducing the NAR architecture able to base its prediction on a high number of regressors. The analysis of performance indicators highlighted an overall good performance in predicting temperature values up to two hours. This enables the design of more accurate control policies based on forecasting thermal behaviors for the energy-efficient management of Smart Buildings, such as Demand/Response, Demand Side Management, and peak-shaving.

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