Preparing Weather Data for Real-Time Building Energy Simulation

Maryam MeshkinKiya[1], Riccardo Paolini[2]
[1]Politecnico di Milano, Milan, Italy
[2]University of New South Wales, Sydney, Australia

Abstract

The application of actual weather data for building performance simulations has become more popular. Yet, anomalous values defect the results, while missing data lead to an unexpected termination of the simulation process. Traditionally, infilling missing values in weather data is performed through periodic or linear interpolations. However, when missing values exceed many consecutive hours, the accuracy of traditional methods is subject to debate. This study demonstrates how Neural Networks can execute highly accurate data imputation for infilling missing values. Results show that Neural Networks provide a reasonable balance between training time and accuracy compared to popular supervised learning techniques.

Introduction

The estimation of the energy performance of buildings is conducted with a variety of different methods and tools. While scientists improve the performance of building energy calculation engines, differences between simulated and real building energy consumption are repeatedly reported (Menezes, Cripps, Bouchlaghem, & Buswell, 2012). This mismatch is known as the performance gap, and different sources are recognized as contributing factors (Bordass, Cohen, Standeven, & Leaman, 2001). Inaccuracy in the inputs of the building energy model is one of the most significant factors affecting the performance gap (De Wilde, 2014; Zou, Wagle, & Alam, 2019).

The inputs of building energy simulations consist of design, climatic and operation parameters (Nagpal, Mueller, Aijazi, & Reinhart, 2019). The climatic parameters are fed to Building Performance Simulation (BPS) tools through weather files in various temporal resolutions. New approaches, including real-time BPS, require actual weather data streams (Cuerda, Guerra-Santin, Sendra, & Neila, 2020; Jentsch, Bahaj, & James, 2008) (Pang et al., 2016). However, using the raw measurements directly from weather stations raises new challenges since these data commonly suffer from anomalous and missing values. Moreover, due to maintenance or instrumental errors, the data needs regular quality control tests to ensure consistency within the weather datasets (Estévez, Gavilán, & Giráldez, 2011).

Given the importance of quality checks, different solutions have been proposed and compared for infilling missing entries in weather datasets, including empirical, statistical and function fitting methods (Kashani & Dinpashoh, 2012). Acceptable performance of empirical (e.g., interpolation) and function fitting methods (e.g., supervised ML techniques) have been studied in the condition of systematic missing values (Kornelsen, Coulibaly, & Asce, 2014). The performance of empirical methods can be affected by the temporal resolution of continuous data, and therefore, poor performances have been reported for infilling missing data within daily profiles (Shabalala, Moeletsi, Tongwane, & Mazibuko, 2019).

Neural Networks (NN) – which can be categorized in the supervised function fitting groups – have been more popular in recent studies of climatic parameter prediction. Most of the studies in this area resort to a network of weather stations to obtain an estimate of missing values. NN has been utilized for imputation of missing temperature, solar radiation, as well as wind speed (Tardivo & Berti, 2012) (Yadav & Chandel, 2014) (Bilgili, Sahin, & Yasar, 2007). The estimation of missing values among the datasets through NN demands a series of reliable samples. Each sample consists of a set of input features and one or more targets. The performance of ML models depends on choosing the proper set of input features, selecting a suitable training function, and gathering adequate samples for training and testing the network (Khayatian, Sarto, & Dall'O', 2016).

As an original contribution, this paper provides a framework for infilling missing climatic values in real-time by resorting to nearby weather stations. Particularly, missing values of two weather parameters, i.e., temperature and relative humidity, are targeted here. It is especially important for real-time building energy simulation, where anomalous and missing values can distort the results or terminate the simulation process. A robust comparison between supervised Machine Learning (ML) techniques is performed to highlight the benefits and drawbacks of NN. The proposed methodology is validated for a network of weather stations in northern Italy. Given that this study presents a general framework for infilling missing values, the proposed method can be extended to other climates and weather stations.

Data description

The hourly measurements of temperature (T) and relative humidity (RH) for nine years (from 2000 until 2008) are collected from seven different weather stations within Milano, Italy (Figure 1). The measured data are extracted from the open repository of ARPA Lombardia ("ARPA Lombardia Agenzia Regionale per la Protezione dell'Ambiente," 2020). While the entire nine years of temperature's data is utilized in this study, an initial analysis revealed an irregular pattern of relative humidity for the period of 2000 to 2004. Therefore, relative humidity is only analyzed and tested for four years (2005-2008). For a primary quality control test on the original data, the anomalous and missing values are (as a standard practice) replaced with the value of "-999". It facilitates distinguishing missing data and outliers, while the entire array can still be treated as a numeric matrix.

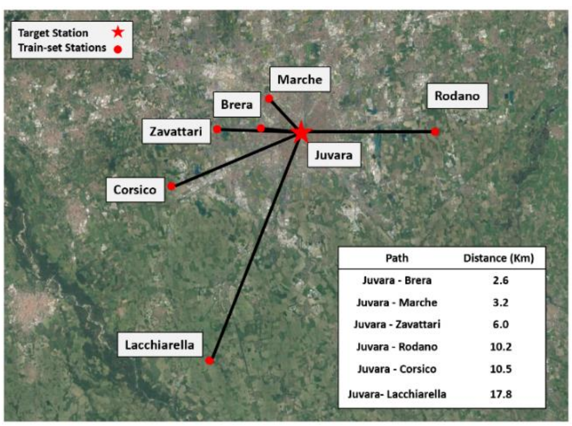

Figure 1- The utilized network of weather stations in Milano (MI, 45.4642° N, 9.1900° E).

Methods

The first step in preparing raw weather data for BPS is performing quality control tests to flag any inconsistency in measurements. Accordingly, the quality control procedures (including range test and relation test) are applied over the selected parameters based on (Estévez et al., 2011). It should be noted that specific thresholds of quality control tests for Milan city are utilized as suggested by (Paolini et al., 2017).

Architecture of NN

Hourly data of temperature or relative humidity are the main features that shape this study's input and target samples. The input features consist of inputs from train-set stations (see Figure 1), including the current time step and two observations immediately preceding the current time step. The date and hour of measurements are also included in the inputs (Table 1). The target of prediction is the hourly observations from "Juvara" weather station (see Figure 1).

In an attempt to find the best group of input features, we observe that missing values (-999) in the input data can notably affect the performance of the NN. This behaviour is because the model cannot ignore anomalous values from other stations that are utilized as input data. To overcome this issue, we add a Boolean vector for each input sample, where the value of "0" corresponds to the anomalous value of "-999", and the value "1" corresponds to non-anomalous measurements. These extra sets of Boolean features are hereafter called Logic Anomaly Indicators (LAI). Therefore, additional vectors with the same size as the main inputs are added to ensure that the weighting procedure will detect anomalies in the inputs while training the neural net.

From Table 1, three categories of input features are visible: (1) samples of measured weather parameters (T and RH), (2) corresponding DateTime of each sample (Month, Day, Hour), and (3) Logic Anomaly Indicators (LAI). Since six weather stations are considered train-set stations (Figure 1), 18 features are assigned to category 1, three features are allocated to the DateTime category, and another 18 features are designated to LAI Boolean indicators. Thus, the total number of input features sums to 39 parameters.

A neural network is set up with one logistic layer consisting of ten nodes with tangent hyperbolic activation function and a final linear layer as output (Figure 2). The network is trained by using the Levenberg-Marquardt optimization algorithm. The missing values (-999) are eliminated from the target dataset to prevent confusion during the training process. Also, the rows containing (-999) in the target are removed from the input dataset and keep the size of the input and target matrices consistent.

Table 1- Input feature for predicting missing T in target station (Same features considered for RH).

Input features	***Comment***
T-in h-2	Temperature in -2 hours of target hour
T-in h-1	Temperature in -1 hour of the target hour
T- in h	Temperature in the target hour
Month (M)	
Day (D)	Date of target hour
Hour (H)	
LAI h-2	
LAI h-1	Logic Anomaly Indicator (LAI) for Th-2, Th-1, Th
LAI h	
Target	***Comment***
T-out h	Temperature in the target hour

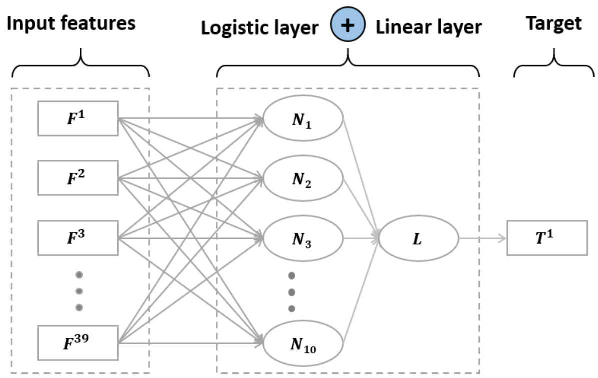

Figure 2 - Diagram of the vanilla neural network utilized in this study.

Other machine learning techniques

Supervised learning is a well-known approach for predicting continuous variables (Rasmussen & Williams, 2006). Like NN, other supervised algorithms use a reliable set of input features and target(s) to train a model for predicting missing values. In this study, we contrast five different regression models against NN. The models are: 1) Linear regression, 2) Regression Tree, 3) Support Vector Regression, 4) Gaussian Process Regression, and 5) Ensemble Tree.

1) Linear regression (LR) is among the popular algorithms to infill missing climatic parameters (Dumedah & Coulibaly, 2011; Kashani & Dinpashoh, 2011; Tardivo & Berti, 2014). This method, also known as multilinear regression, learns a linear fit on multiple inputs to predict targets, which in this study refers to the missing climatic values.

2) Regression Tree (RT) is a widely used ML technique that follows an explore-detect data structure approach (Kim & Pachepsky, 2010). Regression trees divide the root data (inputs) into partitions and learn a prediction model for each partition (Loh, 2011).

3) Support Vector Regressions (SVR) operate based on kernel function techniques and are considered non-parametric models. The method is recognized as one of the most reliable methods for imputation of missing data (Aydilek & Arslan, 2013).

4) Gaussian Process Regressions (GPR) are a sub-category of bayesian ML techniques that find the latent variables to predict the response to input data. Like SVR, these methods are also considered kernel-based and non-parametric models (Rasmussen & Williams, 2006).

5) Ensemble Tree (ET) is a powerful version of decision trees that works through combining other ML techniques such as multiple linear regression to perform a prediction (Seni & Elder, 2010).

All supervised learning techniques, including neural networks, are implemented in MATLAB R2019b. An identical training set is fed to all ML techniques. In all models, 15% of input data is held out during training as the validation set. The methodology of this paper demands separate training models for temperature and relative humidity.

Robustness of the ML models

This study also investigates the robustness of each model encountering extreme events that may affect predictions' performance. Accordingly, three critical periods are separated from the original measurements and used as the test-sets. These periods are daily profiles that are chosen from three representative weeks with extreme events, i.e., (1) peak winter, (2) peak summer, and (3) high fluctuation daily profiles. Furthermore, the chosen test-sets are free of any missing values (-999) in both the input and target datasets. This strategy enables us to evaluate the performance of prediction functions with a dataset not seen during training. Then, missing values are intentionally inserted into the test-set to mimic the presence of anomalous and missing values in adjacent weather stations. Since six adjacent weather stations are included in input features, 64 hypothetical scenarios are necessary to cover all possible combinations of missing values. Given that, we are interested in the least risky performance of the predictors, we focus on the worst performance (highest RMSE) of each model. The worst performance of each ML model can occur in any of the three extreme events mentioned above.

Performance metrics

Using multiple evaluation metrics is a common practice in assessing the performance of ML models since each metric provides a different insight onto the accuracy of models

(Anjomshoaa & Salmanzadeh, 2019). Mean Square Error (MSE), Mean Absolute Error (MAE), Root Means Square Error (RMSE), and Throughput Rate (TR) are the measures considered for evaluating the accuracy of candidate methods (Eq.1-3). The throughput rate is the amount of time that each ML model encodes each sample.

$$MSE = \frac{1}{n}\sum_{1}^{n}\left(Y_{Measured} - Y_{predicted}\right)^2 \qquad (1)$$

$$MAE = \frac{1}{n}\sum_{1}^{n}\left|Y_{Measured} - Y_{predicted}\right| \qquad (2)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{1}^{n}\left(Y_{Measured} - Y_{predicted}\right)^2} \qquad (3)$$

$$TR = Training\ Time/number\ of\ samples \qquad (4)$$

Where $Y_{Measured}$ refers to actual measurements of weather parameters (temperature/relative humidity); and, $Y_{predicted}$ is the predicted values by trained functions.

Result and discussion

Training performance

After the pre-processing stage, the training-sets are fed into all ML models. Training is performed on an Intel 6600U CPU @ 2.60 GHz, while utilizing MATLAB's parallel computing toolbox. Although neural networks can be executed on the Graphics Processing Unit (GPU), this study refrains from using the GPU, to keep consistency between the ML algorithms. It should be noted that the training process is repeated three times for all algorithms, then the lowest performance values and throughput rate are reported. Performance of utilized ML models for temperature and relative humidity are reported in Table 2 and Table 3.

Table 2 - Training performance of ML models for T (°C).

Method	MSE	MAE	RMSE	Throughput (ms)
ET	**0.32**	0.45	**0.56**	0.72
GPR	0.37	0.66	0.61	229.11
LR	0.69	0.70	0.83	**0.06**
NN	0.42	0.49	0.64	0.36
RT	0.46	**0.42**	0.68	0.15
SVR	0.73	0.69	0.86	51.51

It is observed that Ensemble Tree (ET) returns the smallest training error in MSE and RMSE for both temperature and relative humidity. While ET appears as the second-best model based on the MAE of training. Also, training the Linear regression (LR) concludes fastest. The LR is well-recognized as a fast-training method at the cost of lower accuracy. It is visible for both parameters in Table 2 and Table 3, as the LR returns the second-worst training error in all metrics. Gaussian Process regression (GPR) has the second-best performance by MSE and RMSE while being the most time-consuming among all training techniques. On the other hand, NN seems to provide a reasonable balance between accuracy and training time.

Table 3 - Training performance ML models for RH (%).

Method	MSE	MAE	RMSE	Throughput (ms)
ET	**7.44**	1.40	**2.72**	0.71
GPR	10.17	2.23	3.19	42.68
LR	21.68	3.11	4.65	**0.07**
NN	8.87	2.22	2.97	0.25
RT	10.89	**1.08**	3.3	0.18
SVR	23.36	3.00	4.83	28.94

Probability of encountering missing data

It is important to note that reliance on other stations can have its own risks during real-time predictions. Namely, one or more stations used as inputs to the predictor can also be out of order due to maintenance or provide anomalous values. Such occurrences, although less likely, are not impossible. Consequently, the probability of encountering missing data in adjacent stations is evaluated by assessing the data from all weather stations (Table 4). These probabilities are extracted from the entire dataset of T (nine years) and RH (four years) observations. Regardless of which station is out of order, the probability of encountering a single missing value or anomaly from another station is 16% for temperature and 32% for relative humidity. The chances of having more than one station out of order are significantly lower, although still not insignificant (Table 4).

Assessing the robustness of ML models

Specific test-sets are utilized to assess the response of each model facing new sets of data and evaluate the accuracy of trained models. As mentioned, these portions of data are excluded from the original dataset before training. These test-sets are hypothetical scenarios in which a model can face missing observations from one or more of the inputs in weather stations. Table 5 and Table 6 report the highest RMSE of predictions with manually inserted missing values. It is observed that the presence of anomaly and missing values considerably affects the reliability of predictions from all ML models. Low accuracy in the temperature predictions is noted during the extreme summer and extreme winter weeks (Table 5). In contrast, the accuracy of RH’s predictions is worst when a high fluctuation in daily profiles occurs (Table 6). The comparison shows that NN displays the best overall performance for the studied weather parameters amongst the hypothetical scenarios with missing values.

Table 4- Probability of encountering missing data in other weather stations.

	6 missing	**5 missing**	**4 missing**	**3 missing**	**2 missing**	**1 missing**	**No missing**
Temperature	0.012	0.0025	0.0088	0.3	2.5	16.1	81
Relative humidity	0.0076	0.0039	0.027	0.99	6.9	32.5	59.6

Table 5- Comparison between worst accuracy of candidate MLs in extreme conditions; ***Summer****: peak summer;* ***Winter****: peak winter. Lower values correspond to better performance.*

	Method	**6 missing**	**5 missing**	**4 missing**	**3 missing**	**2 missing**	**1 missing**	**No missing**	**Worst RMSE**
	EB	13.7	13.7	11.9	7.5	4.8	1	**0.6**	Summer
	GPR	11.2	14.7	15.1	15	11.8	0.7	**0.6**	Summer
Test-set	LR	**7.1**	7.1	7.1	6.9	6.5	3.7	0.7	Winter
RMSE,	NN	8	**6**	**2.5**	**1.8**	**1.4**	**0.9**	**0.6**	Winter
T(°C)	RT	7.2	7.2	7.2	7.2	7.2	4.2	0.7	Summer
	SVR	7.6	7.8	7.7	7.5	6.9	4.7	0.7	Winter

Table 6- Comparison between worst accuracy of candidate MLs in extreme conditions; ***Oscillation****: high fluctuation in daily profiles. Lower values correspond to better performance.*

	Method	**6 missing**	**5 missing**	**4 missing**	**3 missing**	**2 missing**	**1 missing**	**No missing**	**Worst RMSE**
	EB	9.3	10.8	7.8	5.9	**5.1**	4.5	4.2	Oscillation
	GPR	9.6	25.9	18.1	13.9	11.5	**4.3**	3.7	Oscillation
Test set	LR	10.9	11.2	10.7	10.1	9.4	7.8	3.7	Oscillation
RMSE,	NN	**7.6**	**6.9**	**5.7**	**5.3**	5.6	**4.3**	**3.6**	Oscillation
RH (%)	RT	9.7	14.3	12.9	11.9	6	5	4.2	Oscillation
	SVR	11.3	11.8	11.5	11.1	10.3	8.8	3.9	Oscillation

Limitations and future work

The maintenance of weather stations (e.g., sensor replacements or relocating the instruments) affect the quality of data which are directly reflect to the performance of ML models. Inadequate information about the maintenance of utilized weather stations is one of the limitations of this study. Moreover, the requirement of long-term weather data from multiple weather stations within an urban area is a drawback of this study.

The framework introduced in this study was tested on a particular climate however the performance of the method could vary for other climates, and further assessments are highly recommended. Additionally, implementing the approach into a co-simulation setup (Wetter, 2011) is suggested as the next step to demonstrate the true potential and drawbacks of the method, as suggested in the Supplementary material (Figure 3).

Conclusion

This study introduces a framework for real-time prediction of missing weather data to facilitate online energy simulation. The proposed method (neural network) is contrasted against six other supervised ML techniques. The models are compared based on performance and training time. Also, the robustness of the candidate ML techniques is evaluated through input samples, which are excluded from the training dataset. It is observed that the performance of all models strongly depends on the quantity of the missing values in adjacent stations. However, the neural network proves to outperform all other studied ML techniques. Although the method is proposed for real-time building modelling, it is suitable for constructing multi-year building simulation weather data.

Acknowledgment

This paper is part of a PhD study supported by the scholarship “Borsa per dottorandi di ricerca delle Universitá Milanesi” funded by Fondazione Fratelli Confalonieri.

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Supplementary material

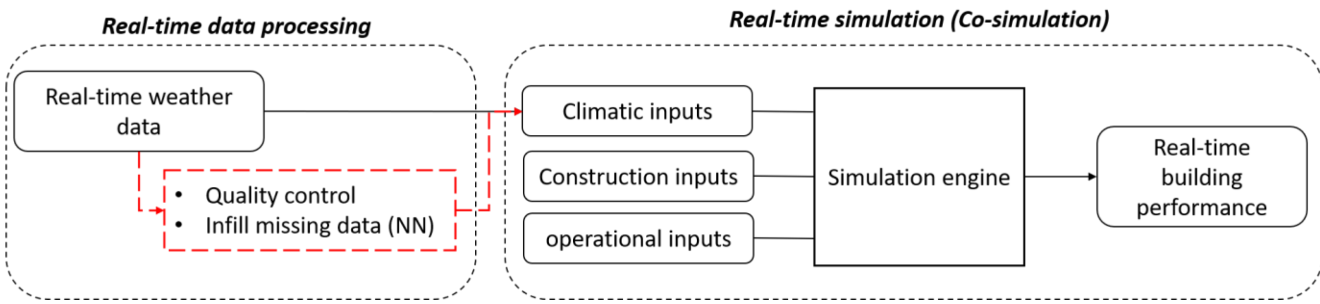

Figure 3- Placement of method of this study (red dashed line) in a real-time building simulation.