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Application of artificial neural networks to the simulation of a Dedicated Outdoor Air System (DOAS)

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Abstract

Tables of performance of installed HVAC (Heating, Ventilation and Air Conditioning) devices are important in the development of consistent building energy audits and appropriate control strategies. However, given the possible complexity of HVAC devices and the need for the deployment to computational environments, tables of performance should be passed in a more complete and flexible format, compared with the current practices in the HVAC sector. In such a context, this paper describes the phases of development and application of Artificial Neural Networks (ANNs) aimed at the assessment of the performance of a Dedicated Outdoor Air System (DOAS). ANNs are well renowned because of their applications in many important fields such as autonomous driving systems, speech recognition, etc. However, they may be used also to calculate the output of complex phenomena (like the ones involved in HVAC components) and are characterized by a very flexible and comprehensive formulation which would be able to adapt to any HVAC component or system. In the frame of this study, three ANNs have been developed and tested, for the full description of the performance of a DOAS. The developed ANNs were trained by means of data coming from a proprietary software. The achieved ANNs showed robust and reliable behavior and ensure high accuracy (mean absolute errors usually below 0.1 K on temperatures and 0.3% on capacity and power) and flexibility. Moreover, in some cases, they may be used also for the identification of anomalous data present among the sets of training and validation data.

Keywords: Artificial Neural Networks; HVAC components; tables of performance.

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1. Introduction

Artificial Neural Networks (ANNs) have often been applied in the field of energetics of buildings. The field mostly interested by the application of ANNs consists in the development of control systems [1]. For instance, Ahmed et al. developed a HVAC Controller using General Regression Neural Network (GRNN) [2], while Yang et al. used neural networks to develop a simultaneous control of indoor air temperature and humidity for an air conditioning system [3]. Analogously, ANNs can be used to monitor the regular operation of HVAC systems, e.g. as reported by Verhelst et al., who analyzed continuous commissioning of HVAC systems by means of ANNs [4] and Du et al., who performed fault detection and diagnosis by ANNs [5].

Another important field of application consists in the development of models based on rich databases about building energy consumption figures and aimed at the forecast of building energy consumption, especially in the case of refurbishment, as shown by Beccali et al. [6], Ascione et al. [7], Deb et al. [8] and Rahman et al. [9].

Last but not least, ANNs can be used to model HVAC systems and components, as described by Jani et al. in the case of a solid desiccant cooling system [10], and by Afram and Janabi-Sharifi [11], Kusiak and Xu [12] and Sala-Cardoso et al. [13].

Modeling of HVAC components by ANNs is the topic of this paper. Moreover, this paper shows how ANNs can be profitably used to exchange performance data in a flexible and accurate way among various software tools. In fact, thanks to their well-structured formulation, ANNs show better fitting performance than usual fitting algorithms. In fact, they can be used to accurately fit data even in case of unfavorable circumstances such as unknown or complex data pattern, multidimensional input and output and noisy data.

This research activity started as a response to the needs of a manufacturer of HVAC components. The company needed to develop a software aimed at the rapid calculation of the performance of a new range of Dedicated Outdoor Air Systems (DOAS), including the operation under part load conditions. In particular, this range of DOAS follows the scheme represented in Fig. 1 and consists in an air-handling unit coupling a rotary heat exchanger for waste heat recovery with an inverter-driven heat pump operating as an additional heat recovery between exhaust air and supply air. Moreover, the supply and exhaust fans are provided with inverter-driven motors varying supply and exhaust air flow rates independently so that, in cooling mode, additional air flow rate can be circulated through the condenser to keep condensation temperature under convenient limits, based on the curve shown in Fig. 2.

The manufacturer already uses a software aimed at the calculation of the performance of common air-to-air heat pumps, starting from the actual tables of performance of each heat pump component. However, it cannot be interfaced with the software calculating the performance of the rotary heat exchanger and could not support the consequent calculation iterations. Moreover, it cannot identify the operating point for given conditions of supply humidity (important for the control of room air humidity in specific cooling contexts) or calculate the most suitable additional air flow rate to be supplied at the condenser to increase the efficiency of the thermodynamic cycle, as mentioned above with reference to Fig. 2.

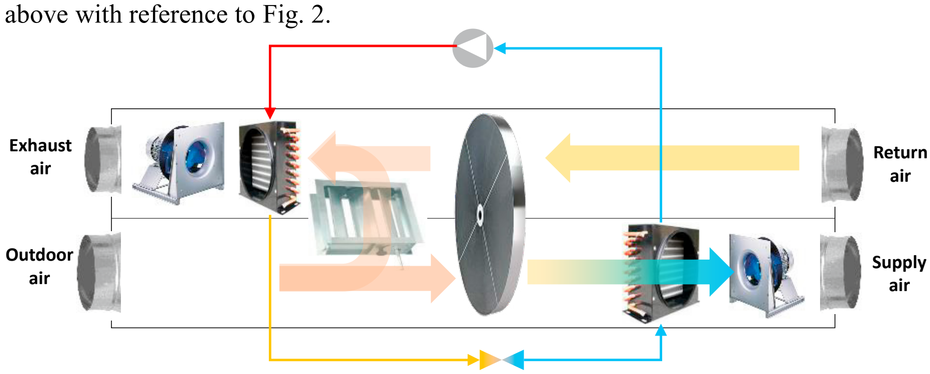

Fig. 1. Scheme of the DOAS under study.

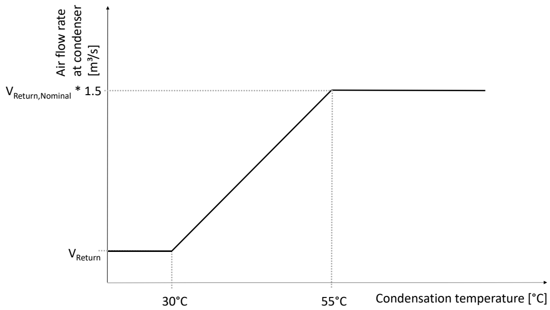

Fig. 2. Assessment of total air flow rate at condenser (i.e. return air flow rate + additional air flow rate) as a function of sensed condensation temperature.

2. Method

2.1. Overview

The present research took advantage of ANNs in the achievement of a software able to calculate the performance of the new DOAS as a whole and to define control strategies aimed at increasing its efficiency.

For this purpose, the following actions were taken (Fig. 3):

A. Generation of tables of performance for the basic heat pump, based on the following parameters:
   - Input parameters listed in Table I, with relevant limits. The limits were defined taking into account extreme operation conditions that may take place in the basic heat pump provided within the air-handling unit represented in Fig. 1.
   - Output parameters:
     - User side - Total thermal power [% of nominal capacity];
     - User side - Sensible thermal power [% of nominal capacity];
     - Compressor - Power consumption [% of nominal power consumption];
     - Condensation temperature [°C];
     - Evaporation temperature [°C];
     - Flag indicating whether the given boundary conditions are physically feasible [-];
     - Flag indicating whether the final condensation and evaporation temperatures are within the admitted operation area of the compressor, based on the recommendations of the manufacturer of the compressor [-].

   An overall number of about 36000 combinations of input parameters were considered for cooling mode and 42000 for heating mode, thanks to the parametric calculation features already embedded in the design software used by the manufacturer.
B. Acquisition of the equation fitting the performance of the rotary heat recovery, based on the following input/output parameters:
   - Input parameters: volume flow rate and intake dry bulb temperature and relative humidity of both the air streams;
   - Output parameters: Sensible efficiency and total efficiency.
C. Development of Artificial Neural Networks (ANNs) aimed at the assessment of the heat pump performance based on the tables of performance generated in A. In fact, ANNs were identified as the most convenient tool to resume and fit the large number of possible combinations given by the number of input parameters and their ranges of variation. In this case, the developed ANNs were trained by means of data coming from proprietary software.
D. Development of the software integrating algorithms described in B and C and embedding additional control strategies and other features.

Table I. List of input parameters and relevant limits.

Parameter	Cooling mode		Heating mode	
	Min value	**Max value**	**Min value**	**Max value**
Rotation speed of the compressor [rps]	20	100	20	110
User side - Air flow rate [% of nominal supply air flow rate]	50	125	50	100
User side - Dry bulb temperature at intake [°C]	18	42	-10	20
User side - Relative humidity at intake [%]	50	50	40	80
Outdoors - Air flow rate [% of nominal supply air flow rate]	60	100	60	100
Outdoors - Dry bulb temperature at intake [°C]	16	32	8	20
Outdoors - Relative humidity at intake [%]	20	60	50	50

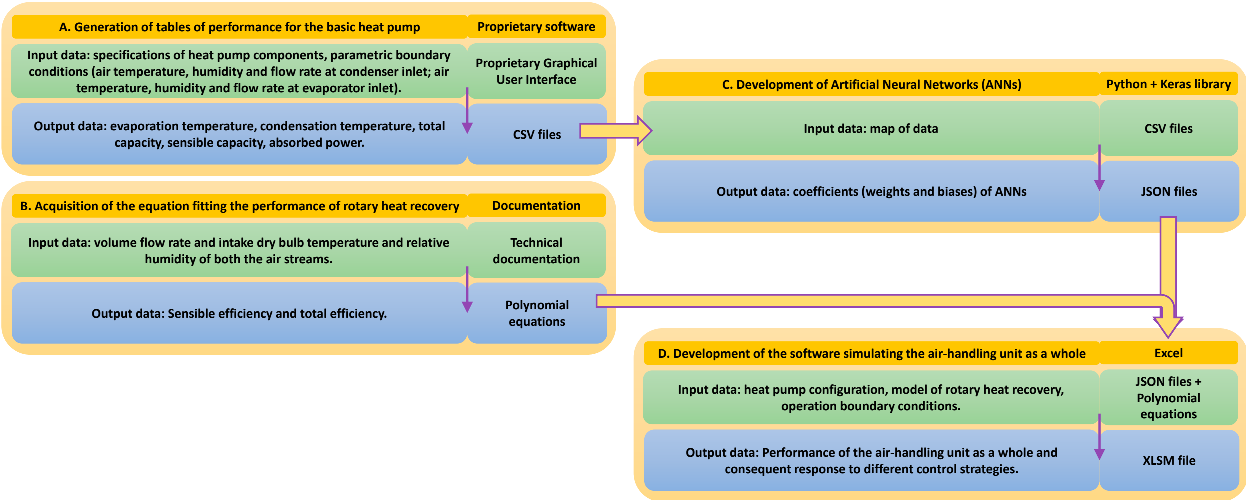

Fig. 3. Workflow of the present research.

2.2. Development of ANNs

Tables of performance are supplied by means of CSV files (one per each heat pump configuration), where each row is an operation point, consisting in 14 parameters (7 input parameters + 7 output parameters).

In particular, three neural networks were developed:

1. ANN for binary classification about the existence of a theoretical operation point at the set boundary conditions. In a few words, input data could imply unfeasible thermal balances, e.g. because of the proportion between set thermal capacity and air flow rates. Boundary conditions allowing the heat pump to operate have operational flag equal to 1, whereas unfeasible boundary conditions have operational flag equal to 0. This ANN is used to quickly check whether the given boundary conditions are feasible. This ANN relies on ReLU (Rectified Linear Unit) and sigmoid activation functions. The target cost function consists in the Binary Cross Entropy, while accuracy is calculated as an additional ANN effectiveness index.
2. ANN for performance assessment. This ANN solves a regression problem (with 7 input parameters and 5 output parameters), relies on ReLU and linear activation functions and is trained solely with operational points belonging to the domain of feasible boundary conditions, according to the definition given in 1. In fact, after positive check from the ANN described in 1, this ANN is trained only by means of significant operation points and is aimed at the assessment of the most important performance indicators of the specific heat pump configuration. The target cost function consists in the Mean Square Error, while Absolute Mean Error is calculated as an additional ANN effectiveness index.

3. ANN for checking whether the operational point belongs to the domain of condensation/evaporation temperatures suggested by the manufacturer of the compressor. As such, this ANN solves a binary classification problem. This ANN relies on ReLU (Rectified Linear Unit) and sigmoid activation functions. It is trained by means of the same data used to train the ANN described in 2. The target cost function consists in the Binary Cross Entropy, while accuracy is calculated as an additional ANN effectiveness index.

ANNs are calculated by a supervised regression machine learning algorithm. This kind of machine learning algorithm allows to fit (regression) a large amount of data based on an input/output correspondence (supervised). As such, the ANN resumes the tables of performance of the heat pump circuit as a black box. For this purpose, a Python program based on open source machine learning library Keras [14] was developed. It makes it possible to parametrically scan different ANN configurations, in terms of number of hidden layers, nodes per hidden layer, activation function, … The developed software tool refines the calculation of bias coefficients and weights for a given number of epochs and stores the best set of bias coefficients and weights which minimizes the target cost function within the given epochs (via the so-called checkpoint storage), thus it gives the best ANN encountered.

Activation functions, weights and bias coefficients of the three ANNs for the specific heat pump configuration are saved into a JSON (JavaScript Object Notation) file, which is suitable for data exchange among different software tools. In this case, the JSON file contains the coefficients of the ANNs, as calculated by means of the developed Python tool, and makes them available to other software tools such as the Excel file developed for the company and embedding VBA (Visual Basic for Application) code.

2.3. Exploitation of ANNs

The latter software tool performs the most important calculations needed by the company's designers for DOAS sizing and performance assessment. In particular, it uses the developed ANNs to calculate the performance of the DOAS as a whole, including the rotary exchanger, depending on parameters typical in system design applications, e.g.: outdoor air temperature and relative humidity, supply air temperature and relative humidity, indoor air temperature and relative humidity, and supply air flow rate. For this purpose, the software tool considers the following boundary conditions:

- Cooling/Dehumidification: the software calculates the rotational speed of the inverter-driven compressor needed to achieve the absolute humidity set for the supply air flow. Moreover, the software tool calculates the additional flow rate that should pass through the condenser to keep a linear correspondence with the condensation temperature, as represented in Fig. 2.
- Heating: the software calculates the rotational speed of the inverter-driven compressor needed to achieve the temperature set for the supply air flow.

3. Results and discussion

3.1. Identification of the best ANN configuration

The software tool developed to generate ANNs brought the authors to identify the following configuration as the best one for the regression ANN defined in 2:

- Type of linking: Fully interlaced
- Number of hidden layers: 2
- Number of nodes per hidden layer: 200

As a reference, Fig. 4 shows how the number of hidden layers and the number of nodes per layer affects the accuracy of the ANN. Fig. 4 shows that:

- Increasing the number of hidden layers improves the accuracy mostly in case of a low number of nodes per hidden layer.
- Most of the accuracy is achieved with about 60 nodes per hidden layer.
- No improvement is achievable in case of more than 200 nodes per hidden layer.

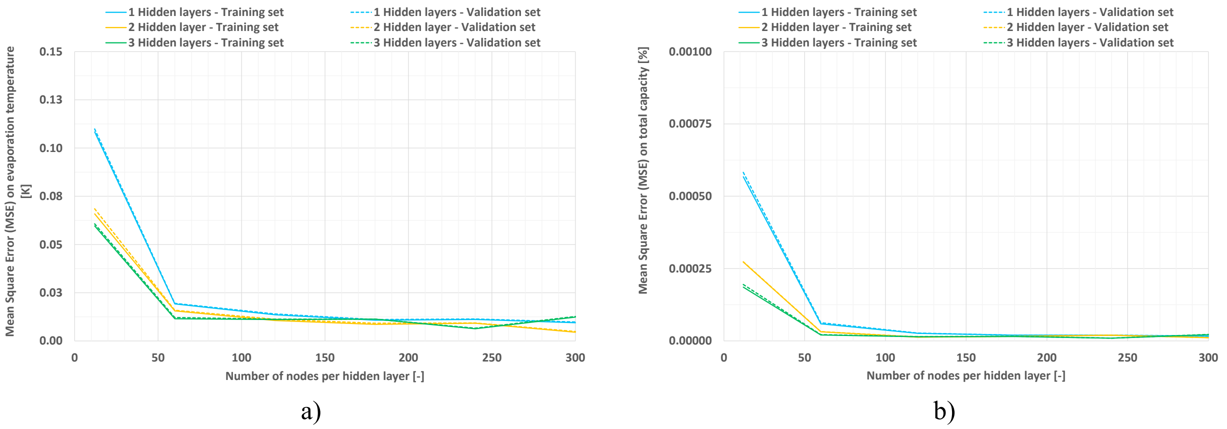

Fig. 4. Target cost function of the ANN depending on the number of hidden layers and the number of nodes per layer, for evaporation temperature (a) and total capacity (b).

3.2. Accuracy of the ANNs

The ANNs achieved showed very high accuracy. In particular, Table II shows errors in an exemplificative ANN, while Fig. 5 shows how these errors are distributed and how the accuracy of the correlation, with reference to the evaporation temperature and the total capacity. It is clear that errors are very low, whichever the set used for calculation, the training one and the validation one. From this one may infer very low possibility of under- and over-fitting around training data.

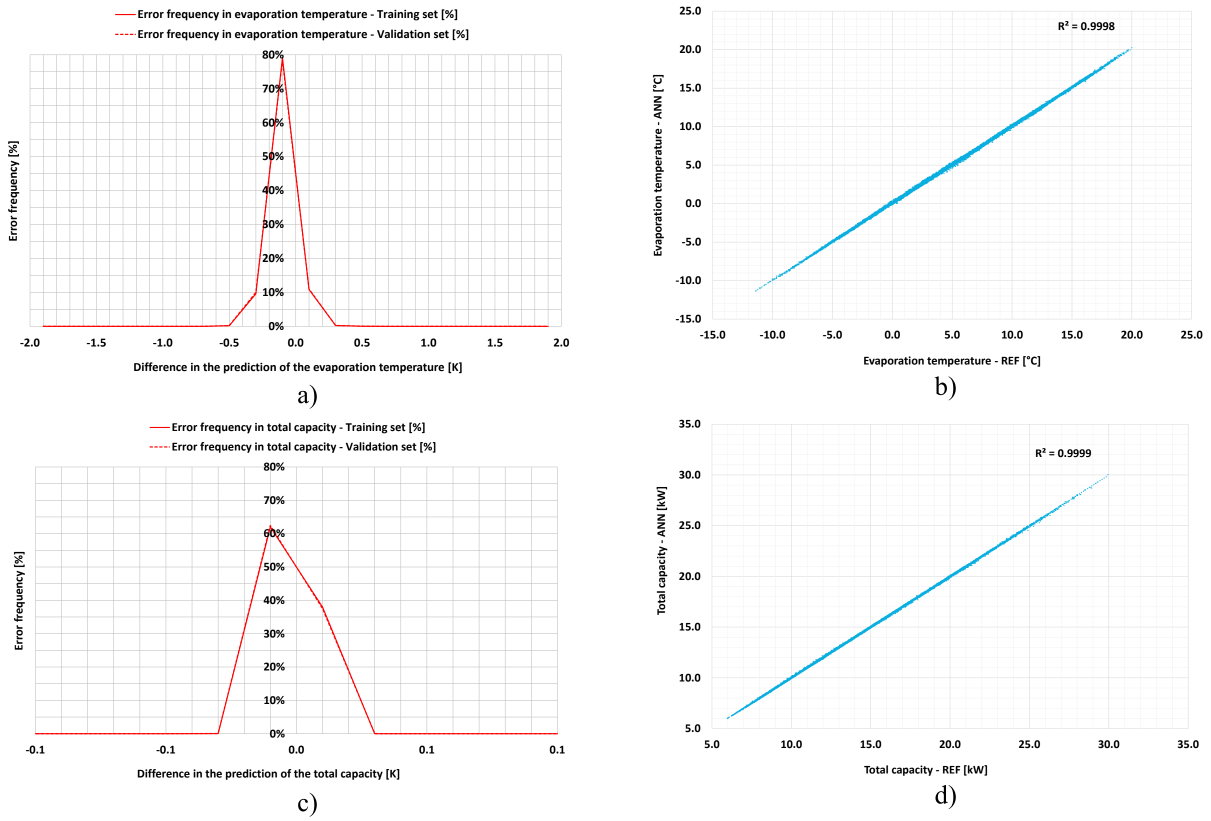

Fig. 5. Error distribution and correlation between ANN outputs and reference data for evaporation temperature (a, b) and total capacity (c, d).

Table II. Example of regression error from ANN application.

Set	Error index	Evaporation temperature [K]	Condensation temperature [K]	Total capacity [%]	Sensible capacity [%]	Absorbed power [%]	COP [%]
Training set	Mean Absolute Error	0.101651	0.067831	0.2199	0.3213	0.2779	0.3304
	Mean Squared Error	0.015553	0.007013	8.73E-04	1.52E-03	1.41E-03	2.02E-03
	Maximum negative error	-0.50599	-0.42256	-2.213	-1.915	-2.423	-3.537
	Maximum positive error	0.529733	0.438091	1.3521	2.0765	1.8694	3.1683
Validation set	Mean Absolute Error	0.103527	0.069047	0.2277	0.3289	0.2865	0.338
	Mean Squared Error	0.016208	0.00734	9.48E-04	1.61E-03	1.55E-03	2.18E-03
	Maximum negative error	-0.51983	-0.36703	-2.191	-1.928	-2.334	-3.955
	Maximum positive error	0.444907	0.340627	1.4361	1.9392	2.8675	2.2407

3.3. Use of ANNs to check the reliability of starting data

An additional use of ANNs consists in their use intended to check anomalies in the starting data. A quick reference to the present case might help in understanding such a collateral use. As said above, the training of the ANNs relies on data parametrically outputted by a software solving the heat pump energy balance based on the specific characteristics of each component. However, this kind of software tools, even if tested for years, still suffers some bugs resulting in anomalous outputs in some conditions. In particular, in the course of this research, the authors found that boundary conditions which were close to each other gave very different outputs, probably because of numerical instability issues. This anomalous behavior was found while checking the accuracy of the developed ANNs. In fact, in some sparse points, the gap between starting data and ANN outputs was anomalously high. A further analysis on the data showed that around these points the profile of ANN outputs has a smooth profile, whereas the starting data show sudden fluctuations, as shown in Fig. 6, where the spike reaching -30°C is clearly an anomalous datum, when compared with the surrounding operational points, by varying the air temperature at the condenser inlet and the air flow at the condenser side. To sum up, while the starting data may incur calculation issues at particular working conditions (even close to working conditions not raising anomalous results), the outputs of ANNs are the result of the concurrent outputs of many contiguous working conditions and, as such, a balance of them. As a consequence, in this context, ANNs were useful also to identify anomalous data included in the calculation domain. Of course, this is useful only if the output parameters are considered continuous and the resolution of the domain mesh is not coarse.

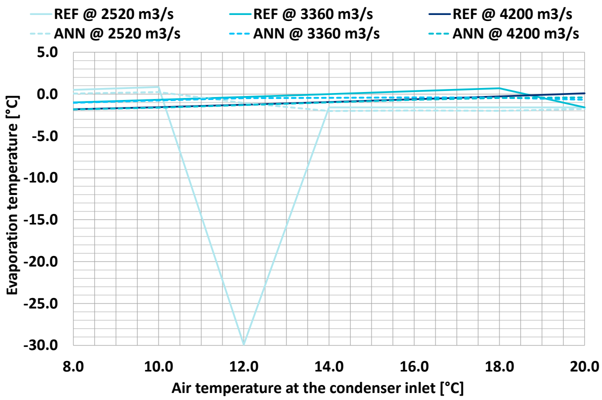

Fig. 6. Example of anomalous reference data that can be identified by means of application of ANNs.

4. Conclusions

This research showed how ANNs may be used for easily sharing data about HVAC components and hence for modelling complex HVAC systems.They are robust and reliable, as they ensure high accuracy (mean absolute errors usually below 0.1 K on temperatures and 0.3% on capacity and power) and flexibility. Moreover, in some cases, the possibility to achieve outputs as a balance of concurrent data from surrounding operational points may makes ANNs useful also for the identification of anomalous data present among the sets of training and validation data.

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