Energy & Buildings 174 (2018) 199–213

Contents lists available at ScienceDirect

Energy & Buildings

journal homepage: www.elsevier.com/locate/enbuild

Neural network based predictive control of personalized heating systems

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ARTICLE INFO

Article history:
Received 9 February 2018
Revised 25 May 2018
Accepted 17 June 2018
Available online 30 June 2018

Keywords:
Personalized heating
Automatic control
Predictive control
Machine learning
Artificial neural network
NARX

ABSTRACT

The aim of a personalized heating system is to provide a desirable microclimate for each individual when heating is needed. In this paper, we present a method based on machine learning algorithms for generation of predictive models for use in control of personalized heating systems. Data was collected from two individual test subjects in an experiment that consisted of 14 sessions per test subject with each session lasting 4 h. A dynamic recurrent nonlinear autoregressive neural network with exogenous inputs (NARX) was used for developing the models for the prediction of personalized heating settings. The models for subjects A and B were tested with the data that was not used in creating the neural network (unseen data) to evaluate the accuracy of the prediction. Trained NARX showed good performance when tested with the unseen data, with no sign of overfitting. For model A, the optimal network was with 12 hidden neurons with root mean square error equal to 0.043 and Pearson correlation coefficient equal to 0.994. The best result for model B was obtained with a neural network with 16 hidden neurons with root mean square error equal to 0.049 and Pearson correlation coefficient equal to 0.966. In addition to the neural network models, several other machine learning algorithms were tested. Furthermore, the models were on-line tested and the results showed that the test subjects were satisfied with the heating settings that were automatically controlled using the models. Tests with automatic control showed that both test subjects felt comfortable throughout the tests and test subjects expressed their satisfaction with the automatic control.

1. Introduction

Individualized conditioning systems in commercial buildings are able to provide an improvement in the thermal comfort of occupants while reducing energy consumption [1–5]. Building occupants have a different perception of the thermal environment and what they perceive as a comfortable environment differs due to individual differences (e.g. gender, age, body composition) [6,7]. Previous studies showed that individuals with different body composition react differently to the same thermal environment [8–11]. Personalized local conditioning systems provide the option that every user can create their own environment based on their individual comfort requirements and preferences. The interaction of the user with personal conditioning systems is explained in detail in the study by Verhaart et al. [12]. Personal conditioning systems are mostly user controlled where users determine the heating or cooling setting of the system at any given time [13].

Studies by Brager et al. [14] and Boerstra et al. [15] showed that having personal control over the thermal environment has a positive impact on perceived comfort. In another study by Boerstra et al. [16], it was shown that perceived control was higher in the session where occupants had control over their desk fan, but there were no differences in perceived thermal comfort between the sessions with control and without. On the other hand, self-reported and objectively measured performance was better in the session with no control [16].

The benefit of automated control in personalized conditioning systems is that it can enhance concentration of occupants, and prevent inefficient energy use as well as thermal sensation overshoot [13,17]. A method for automated control of personalized conditioning system using control equations was introduced by Vesely et al. [13].

In commercial buildings, the most commonly used control method is still proportional-integral-derivative (PID) control and on/off control [18,19]. However, recently many simulation and ex-

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https://doi.org/10.1016/j.enbuild.2018.06.033

perimental research showed that model predictive control (MPC) provides a higher quality of control performance in terms of lower energy consumption while providing optimal thermal comfort [20]. Modeling in MPC can be divided into physical-based modeling (white box) and data-driven modeling (black box) method and the combination approach called grey box [20,21]. Artificial neural network (ANN) as a data-driven technique is a widely used method for building energy prediction and HVAC system control [22–24].

In recent years, machine learning methods were suggested in a number of areas including the building environment [25,26]. Machine learning algorithms are applied for predicting short-term peak electrical demand [27], developing occupancy prediction model [28] or predicting building energy consumption [29]. There are also studies where machine learning models such as neural network models are applied for control of heating, ventilation and conditioning systems (HVAC) [30–32].

A method using support vector machine classifiers was proposed by Megri and Naqa [33] to improve prediction of thermal comfort indices. In a study performed by Kariminia et al. [34], extreme learning machine approach was shown to be a good method to accurately predict visitors' thermal sensations in public urban places. Dai et al. [17] suggested applying the trained predictive model to control heating and cooling systems. Zhao et al. [35] introduced a data-driven individualized complaint model using a multi-linear-class classifier that can be used for individual comfort control and indoor environment set-point control. Michael et al. [36] created predictive models of core body temperature and local skin temperature by applying neural network algorithms. A neural autoregressive network with exogenous input (NARX) model for prediction of the indoor temperature of a residential building was developed by Mechaqrane and Zouak [26].

Neural network modeling is often applied in the building sector as part of model-based predictive control for HVAC systems [37]. Mustafaraj et al. [38] looked at the potential of using neural network was investigated to predict room temperature and relative humidity for different time scales ahead. As a follow up of this study, Mustafaraj et al. [39] proposed a neural network model in order to predict the room temperature and relative humidity in an open office in a modern building.

An increasing number of studies are investigating how machine learning methods can be utilized for predicting thermal comfort needs as well as personal thermal comfort. In the study performed by von Grabe [37], the potential of neural networks to predict the thermal sensation votes under varying conditions was tested. Liu et al. [32] created a neural network model based on the back propagation algorithm for evaluation of individual thermal comfort. The result showed that the neural network model that predicts individual comfort can be an important part for control strategy the air conditioners [32]. Chen et al. [40] presented a novel dynamic thermal sensation (DTS) model that is used as a part of the model predictive control of HVAC systems. The model predictive control was based on the DTS model and it was evaluated in chamber experiments [40]. In order to determine thermal state of an occupant in a built environment, Chaudhuri et al. [41] developed a Predicted Thermal State (PTS) model. The model was created using skin temperature and its gradient together with machine learning classifiers (Support Vector Machine and Extreme Learning Machine). A different approach was introduced by Lee at al. [42] where a novel Bayesian modeling was used as a method for learning individual occupants' thermal preferences.

Kim et al. [43] created personal comfort models using machine learning algorithm that predicts individual' thermal comfort responses. In the study by Kim et al. [43], for developing personal comfort models occupants' behavior with PCS chairs was used as an input to predict individuals' thermal preference. Machine learning algorithms were tested to solve multiclass classification problems of an occupant's thermal preference ('warmer'/'no change'/'cooler') [43].

Until now, machine learning models were successfully demonstrated in many fields as presented earlier. However, to the best of our knowledge, there are no studies that use machine learning methods to predict individual settings of personalized heating systems. Furthermore, there are limited studies that focus on the on-line implementation of such predictive models. Therefore, this paper aims is to apply a learning method for the prediction of individual models to control personalized heating system. The main focus is on developing models using machine learning algorithms that will be able to predict individual settings of the personalized heating system and on-line implementation of created predictive models.

The remaining sections of this paper are structured as follows: Section 2.1 provides details of the methodology which includes the method and data type collected. Section 2.2 provides details on the predictive models that were developed using machine learning method (artificial neural network) using the collected data. The nonlinear autoregressive neural network with exogenous inputs (NARX) is also described in more details in this section. Section 2.3 presents a description of other machine learning techniques that were tested and compared to NARX. In Section 2.4 on-line implementation of the predictive model is presented. In Section 3, the results and discussion of the different machine learning algorithms to find the optimal solution is provided as well as the results of the on-line implementation. In Section 4, the conclusions of this research are presented.

2. Methodology

2.1. Experiment–data collection

Data collection is the first step in developing the prediction model and demonstration of the feasibility of the machine learning model to predict the settings of the personalized heating system. An experimental study was conducted in order to collect the data used for the learning algorithm. Experiments were conducted in the climate chamber of Department of Built Environment, Eindhoven University of Technology. The set-up of the climate chamber is shown in Fig. 1. The dimensions of the climate chamber where all tests were conducted is $3.6 \times 5.7 \times 2.7$ m^3. The outside air was conditioned by an air-handling unit and was supplied from two positions in the room, via a slit on the top of the room and the bottom along the whole width of the room. The air exhaust was positioned at the top of the opposite wall.

Two healthy female test subjects participated in the experiment. The test subjects were informed about the purpose and the procedure of the experiment before the start of the tests and they signed a consent form. Prior to the experiment, body weight, height, and a 4-point skin fold measurements were obtained to determine the body composition of each test subject. The fat percentage was obtained according to Durnin and Womersley [44]. The basal metabolic rate (BMR) was calculated according to Cunningham [45].

Their body characteristics and age are presented in Table 1. The test subjects wore typical winter indoor clothing. During all tests, the average clothing insulation was 0.75 ± 0.03 clo for test subject A and 0.89 ± 0.04 clo for test subject B.

All the tests were performed during winter in January and February 2017. The experiment included in total 28 test sessions with each session lasting 4 h. Each test subject participated in 14 test sessions, one test session per day. Each experimental session started with an acclimatization period in the climate chamber of approximately 10 min during which test subjects prepared their

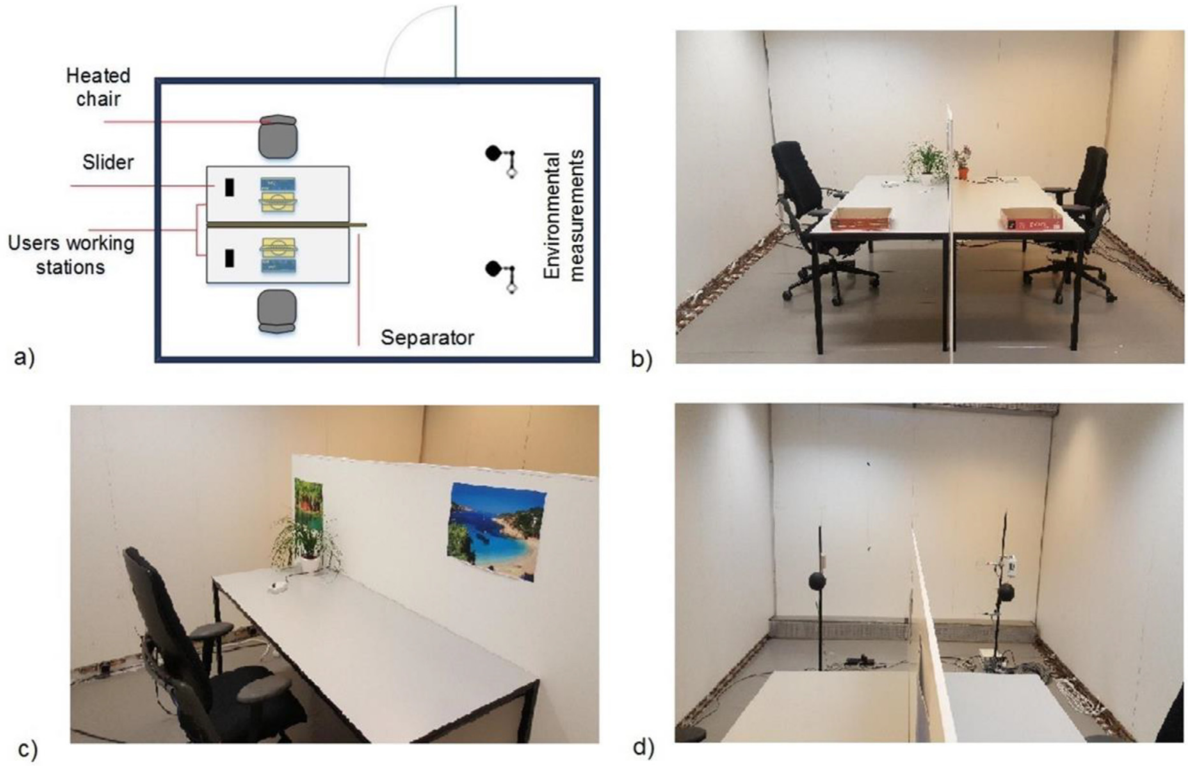

Fig. 1. Climate chamber set up: (a) schematic view of the climate chamber, (b) view of the two user's desk in the climate chamber, (c) close-up of the one desk with the slider and the chair, (d) position of the environmental measurement stand in the climate chamber.

Table 1
Anthropological characteristics of the test subjects.

Test subject	Gender	Age	Weight (kg)	BMI	Fat percentage (%)	BMR (W/m^2)
A	F	29	57	26.7	34.9	38.2
B	F	29	62	22.9	27.8	38.6

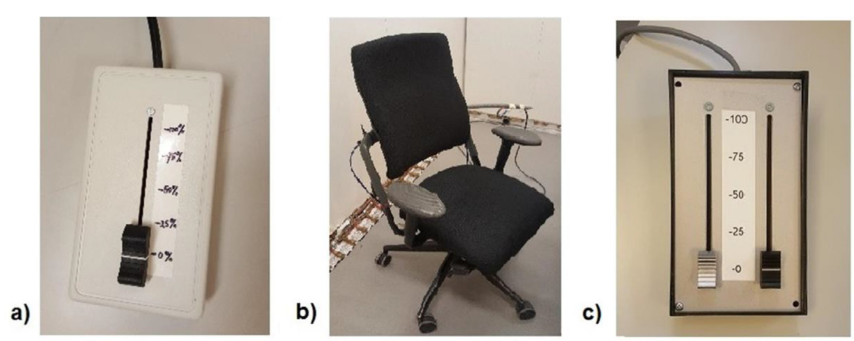

Fig. 2. (a) Slider, (b) heated chair, (c) slider for on-line implementation.

work station. The acclimatization was followed by a four-hour test in the climate chamber. During the experimental session, the test subjects performed typical office work on their computer. They were allowed to drink and eat during the test, and leave to use the toilet if needed. Test subjects were encouraged to adjust the setting of personalized heating at any time in order to be thermally comfortable.

For the experiment, a heated chair (Fig. 2b) was used as it has been shown to be an effective personalized heating system in several studies [2,13,46]. Maximum power of the heated chair was 36 W. The two heated mats were integrated under the fabric surface of the chair seat (40×28 cm^2) and backrest (30×28 cm^2). The heated chair was controlled by the user during the tests with an interface (slider) as shown in Fig. 2(a). The position of a slider related to the control voltage between 0 V and 2 V (0% –100%). The setting of personalized heating during the tests was logged via Labview with one second intervals.

During all tests, air temperature, relative humidity, air speed and black globe temperature were measured and logged every second. As shown in Fig. 1(d), the measurement instruments were attached to the environmental measurement stand. The attached instruments were three air temperature sensors, three anemometers, three relative humidity sensors and a black globe temperature sensor. The black globe was positioned at height of 0.9 m and air temperature, air speed, and relative humidity were measured at three heights of 0.1, 0.7 and 1.1 m.

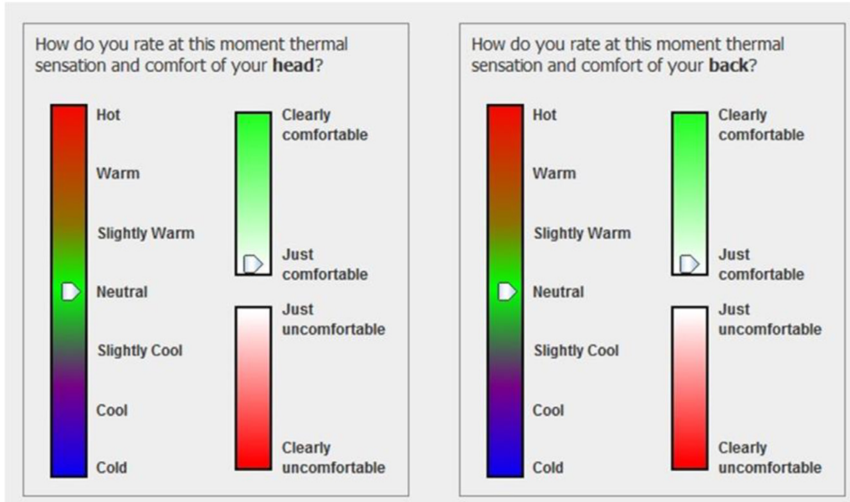

Fig. 3. Questions of the head and back thermal sensation and comfort in the computer-based questionnaire.

Subjective perception of the thermal comfort, thermal sensation and their well-being during all tests was evaluated using questionnaires via a computer app installed on the laptops that test subjects were using. The questionnaire was a modified version of the one that was already developed by Vesely et al. [13]. The questionnaire included questions about clothing, thermal sensation (overall, head, back, hands and feet), thermal comfort (overall, head, back, hands and feet), and well-being. Well-being questions include air quality and self-estimated productivity. To evaluate thermal comfort and thermal sensation the ASHRAE 7-point scale was used. The well-being questions included air quality and self-estimated work performance. During the experimental session, the questionnaire of thermal comfort and thermal sensation was filled every 15 min. The questions concerning the test subjects' well-being were filled in every one hour. Fig. 3 shows the example of the question tab of the questionnaire.

2.2. Machine learning-artificial neural network

The use of the artificial neural network (ANN) for control and optimization has been increasing and it can be applied to both linear and nonlinear relationships between inputs and outputs [47]. For a time series prediction, dynamic neural network is very suitable [48]. In this study, a dynamic recurrent ANN architecture called a nonlinear AutoRegressive network with exogenous inputs (NARX) was used for dynamic prediction of personalized heating settings. The NARX network is a powerful modeling and validation tool that offers simplicity and flexibility of network architecture, time series predictions, as well as fast and accurate training [49]. The equations for the NARX model can be expressed as follows [47,50]:

$$y(t) = f[y(t-1), y(t-2), \ldots, y(t-n_y), u(t-1), u(t-2), \ldots, y(t-n_u)] \tag{1}$$

$$u = [u_1(t) \ldots u_r(t)]^T \tag{2}$$

$$u = [y_1(t) \ldots y_m(t)]^T \tag{3}$$

where

u = input of the network at time t,
y = output of the network at time t,
n_u = input memory order,
n_y = output memory order,
r = number of inputs,
m = the number outputs.

A nonlinear function f describes the systems behavior and in the case of NARX network it is approximated by a Multi Layer Perceptron [49,50].

To create a personalized model that predicts settings of the personalized heating system, two different NARX networks (for subject A and B) were created using the individual data of each test subject collected in the experiment. The NARX networks were created using Matlab 2017a.

The experimental data for each test subject consisted of data collected during 14 test sessions. The data that included inputs and outputs were separated into two parts. The first part consisted of 13 sessions that were used for training, validation, and testing with the optimal NARX architecture. The majority of data session were used for training because larger training datasets reduce the chance of overfitting [37]. Overfitting occurs when the trained network memorized the data used in the training and all the training points are well fitted but when the new data is introduced the error is large [48]. Overfitting means the model is incapable of generalizing in the new situations [51]. Early stopping is a method for improving generalization and it is automatically provided in Matlab for all ofsupervised network creation functions [48].

The second part represents unseen data that was independent of the other data used for training. It consisted of a randomly selected session used to assess the performance of the trained model predicted with the new data.

The inputs for the model were environmental conditions (air temperature, humidity, and radiant temperature) and the output to be predicted were the setting of the personalized heating setting. Considering practical measurements and applying the model it was desirable to minimize the number of input features that were used to train the model. The setting of the heating system corresponded to the control voltage of the slider between 0 V (0%) and 2 V (100%), where 0 V translates to heating was off and 2 V to the maximum power of the personalized heating system. The control voltage was used as the target of the predictive model.

The collected data was available as 14 sessions and each session lasted four hours. This means that the data was not available in one long sequence but as several short sequences. For these cases, to avoid discontinuity in the data, fourteen sequences of four hours were combined in a concurrent set of sequences using the

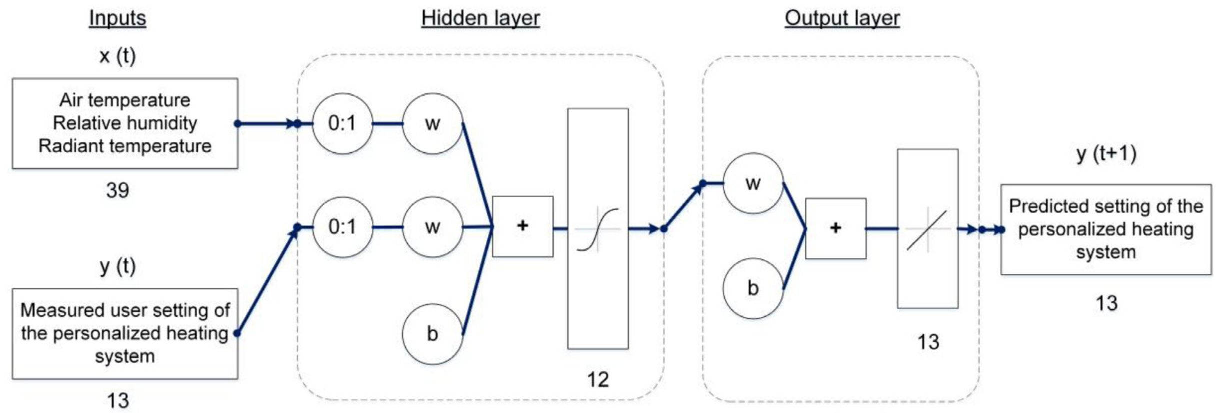

Fig. 4. The architecture of the NARX for predicting settings of the personalized heating system elements with one hidden layer that includes 12 hidden neurons, where w and b are adjustable network parameters called weights and biases (based on [48]).

catsamples function in Matlab. The data were then averaged for every 10 s, representing the setting of the heated chair every 10 s. The input environmental data (air temperature, relative humidity, and radiant temperature) was averaged for every 10 s as well.

NARX network can have two different configurations, parallel and series-parallel architecture. In case of parallel architecture, the output of the NARX network that is estimated is fed back to the input of the feedforward neural network [48]. Since in this study, the real output was available during the training of the network a series-parallel architecture (open-loop form) was created. The real output was used instead of feeding back the estimated output. In this way, a more accurate input to the feedforward network was provided and the created network had a complete feedforward architecture [48]. Neural networks can have a different architecture that is defined by a number of hidden layers and hidden neurons. The example of the architecture of the NARX neural network used in this study is shown in Fig. 4. The network consists of the input layer of the network that includes three input features (air temperature, humidity and radiant temperature), hidden layer that consisted of hidden neurons, and the output layer includes one output target (setting of the personalized heating system) network, respectively. During the training the actual target values are feed back to the network.

The transfer function for hidden layers was a tangent sigmoid transfer function and for the output layer was linear transfer function. A common procedure is to preprocess the data to ensure faster and efficient training. The network inputs and targets were normalized and scaled so that they fell in the range [−1,1] when the input processing function "mapminmax" in Matlab is utilized. The trained neural network then provided outputs in the range [−1, 1]. These outputs were reverse-processed with the same processing function back into the same units as the original targets. The Levenberg–Marquardt back-propagation method was selected for training the developed neural network using a training algorithm programmed in Matlab R2017a, Statistic and Machine learning toolbox [48]. The aim of the Levenberg–Marquardt back-propagation is to minimize the mean squared error (MSE) between the outputs of the network and the targets [36]. The training is stopped when generalization stops improving. More details on the Levenberge–Marquardt back-propagation and training parameters can be found in [48].

In this study, various configurations were tested by varying the number of hidden neurons (2, 6, 8, 10, 12, 14, 16 and 18) in order to find a network with optimal performance. Eight different networks were created for each test subject to represent individual predictive model using collected data. The various architectures of the neural network were investigated in order to find an optimal one. An optimal network was generated for both individual test subjects, providing individual predicting models.

The neural network was fed with training data that consisted of 1441 data points for each of the 13 sessions. This meant 18733 entry points for each individual model. To avoid overfitting a commonly used method during training neural network models consists of randomly dividing available data into three subsets: training, validation and test set [48]. In this case, the available training data (13 sessions) is randomly divided as follows: 70% of the data were used for training, 15% of the data for testing and 15% of the data for validation.

The accuracy of the network was first assessed by looking into performance during training and the accuracy of the network predictions with the unseen data. In order to optimize network performance, a performance function was defined during training that tuned the values of the weights and biases. The performance function was a mean squared error (MSE), which was used to assess the performance of the neural network. MSE represents the calculated error between outputs of the network and targets.

The performance of the created neural network model with the new unseen data was assessed with two calculated metrics. Root mean square error (RMSE) was used to evaluate the prediction accuracy and express average model prediction error Eq. (1), and the Pearson correlation coefficient (PCC) was calculated to show the degree of linear correlation between the real value and the predicted value [29].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(A_i - P_i)^2} \tag{4}$$

where n is the number of multi-steps prediction, A_i is the real value for the time-step i and P_i is the predicted value of the model at the same time-step.

2.3. Other machine learning techniques

2.3.1. Nonlinear autoregressive (NAR) network

The nonlinear autoregressive (NAR) network is used to predict a time series from past values. The performance of the NAR network was investigated and compared to the NARX model. The advantage of NAR and NARX network is that they can be fed with dynamic data in the form of time series sets [52]. Compared to NARX that needs inputs and past outputs, the NAR model uses the past output values of the time series to predict future values [53,54].

The expression for the NAR model can be written as follows [54]:

$$y(t) = f[y(t-1), y(t-2), \ldots, y(t-d)] \tag{5}$$

Table 2
Features of the neural network models.

Characteristics	NARX	NAR_1	NAR_2
Inputs	Air temperature Humidity Radiant temperature	–	–
Outputs (targets)	Setting (intensity) of the personalized heating system	Setting (intensity) of the personalized heating system	Setting (intensity) of the personalized heating system
Data	Averaged every 10 s	Averaged every 10 s	Averaged every 5 min
Evaluation metrics	MSE, RMSE, PCC	MSE, RMSE, PCC	MSE, RMSE, PCC

The Eq. (5) describes a NAR network's function to predict series target y(t) given d past values of y(t) [54].

The data was used in the same manner as when NARX model as created. The output data that represents the output to be predicted were the setting of the personalized heating setting. For training, validation and testing of the neural network model, 13 sessions were used. One session was left as independent to test the trained model with the new unseen data. With the NAR we created and compared two different trained models for each individual. The first one that will be referred as NAR_1 was fed with the data averaged every 10 s as in NARX models. The second model that will be referred NAR_2 was fed with the data averaged every five minutes. The summary of the characteristics of the models can be seen in Table 2.

As in the NARX model, for the NAR network the Levenberg–Marquardt back propagation procedure was implemented. The data was prepared in the same manner as previously described for the NARX model and was randomly divided as follows: 70% of the data were used for training, 15% of the data for testing and 15% of the data for validation. Randomly dividing available data into three subsets: training, validation and test set is commonly used to avoid overfitting [48]. Six configurations were tested by varying the number of hidden neurons (8, 10, 12, 14, 16 and 18) and were compared with the best-performed configuration of the NARX model.

2.3.2. Regression techniques for machine learning

In this paper so far neural network algorithms (NARX and NAR) were tested; however, there is a wide variety of algorithms in machine learning. Furthermore, four different machine learning algorithms that aim to solve regression problem will be tested and compared. Since the aim is to predict settings of the personalized heating chair that is a real value output, the learning problem is considered a regression problem. The selected regression techniques tested are: Support Vector Regression (SVR), Gaussian process regression (GPR), Bagged trees and Boosted trees.

The main idea behind the ensemble algorithms is to combine "weak" learners and their strengths in order to create higher-performance ensemble model [55,56]. Bagging and boosting are main techniques that are part of an ensemble together with the basic learner [55]. More information about bagging and boosting methods can be found in [57]. Two ensemble methods for regression were tested in this study. Boosted trees that consist of the least squares boosting (LSBoost) procedure together with decision trees [56]. The other procedure is bagged trees that use bagging technique with decision trees [56].

Support vector machine (SVM) analysis is a popular machine learning method that can be applied for classification and regression [56,58–60]. The idea behind the SVM to find an optimal separating hyperplane with a maximum margin [58]. SVM regression depend on kernel function and is considered a nonparametric technique [56]. Support vector regression (SVR) is an efficient method that is used for regression problems. In this study, Matlab 2017a regression learner was used to test SVR that implements linear epsilon-insensitive SVM (ε-SVM) regression. The ε-insensitive loss function is representing training error [56].

Table 3
Characteristics and settings of tested algorithms.

Algorithm		Characteristics	Individual model A	Individual model B
SVM Kernel function	Fine Gaussian (SVR_FG)	Kernel scale	0.5	0.5
		Box constrain	1.4	0.712
		ε-insensitive loss	0.04	0.071
	Medium Gaussian (SVR_MG)	Kernel scale	1	1
		Box constrain	1.4	1.712
		ε-insensitive loss	0.04	0.071
	Coarse Gaussian (SVR_CG)	Kernel scale	7	8
		Box constrain	1.4	1.712
		ε-insensitive loss	0.04	0.071
GPR Kernel function	Rational quadratic (GPR_RQ)	Kernel scale	1040	1000
		Kernel sigma	0.260	0.365
	Squared exponential (GPR_SE)	Kernel scale	1040	1000
		Kernel sigma	0.260	0.365
	Matern 5/2 (GPR_M)	Kernel scale	1040	1000
		Kernel sigma	0.260	0.365
	Exponential (PPR_E)	Kernel scale	1040	1000
		Kernel sigma	0.260	0.365
Boosted trees		Minimum leaf size	8	8
		Learning rate	0.1	0.3
		Number of learners	80	70
Bagged trees		Minimum leaf size	8	8
		Number of learners	60	30

Gaussian process regression (GPR) is a nonparametric probabilistic learning method based on kernel function [56,61]. The Gaussian process aims to describe the distribution of the unknown target function that is characterized by its mean function and kernel (covariance) [62,63]. In this study, four different common covariance functions [56] were tested. The settings and features of tested algorithms are presented in Table 3.

10-fold cross-validation was used to randomly split the data into training and test sets to estimate the predictive performance of a model. The data used for training contained 13 sessions and one session was left as independent to test the model with the unknown data. The data were averaged every 10 s. The performance of the models was evaluated in the same manner as previous algorithms. In order to use regression to predict time series, time-based feature (seconds) was used as an input (predictors) together with three other inputs (air temperature, radiant temperature and humidity).

2.4. On-line implementation of the predictive model

The validation of the predictive model accuracy and automatic control effects were evaluated in the on-line implementation. Experiments were conducted in order to test the predictive model in real time with tests subjects in November and December 2017. For the on-line implementation LabVIEW in connection with Matlab was used as shown in Fig. 5.

The same test subjects (A and B) participated in on-line testing. The average clothing insulation during these series of test was

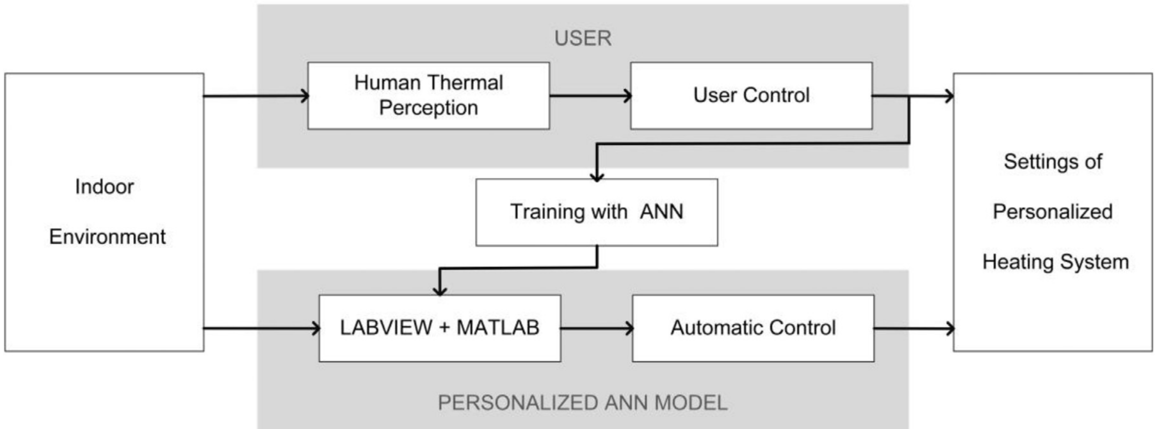

Fig. 5. General control framework.

0.72 ± 0.05 clo for test subject A and 0.92 ± 0 clo for test subject B. The on-line validation of the predictive model consisted of 12 tests, each test subject participated in 6 tests. During 3 test the settings were predicted with the model and the test subjects could not change the settings. After that, 3 tests were performed with combined control. This meant test subject could overrule predictive control if they wanted a different setting. When they moved the right side of the slider (Fig. 2c) the system would take into account the new setting provided by the test subject. When they moved the right side of the slider to 0, the predictive control would take over without taking the user input into account

The setting of personalized heating during the tests was predicted every 10 s. During the tests, the test subjects could see the predicted setting of the heated chair on the left side of the interface (Fig. 2c). The settings of a slider corresponded to the control voltage between 0 V and 2 V (0%−100%).

Thermal environmental data were measured and logged in the same manner as in the experiments during data collection described in Section 2.1. Test subjects answered the same questionnaire every 15 min during the test sessions.

Selected predictive model for test subject A was the one with 12 hidden neurons and for test subject B the model with 16 nodes. These models showed the best results in off-line validation as showed in Section 3.2.1.

3. Results and discussion

3.1. Experiment results-data collection

The indoor environment during all test had an average air temperature of 20.1 ± 0.03 °C, relative humidity of 36 ± 1% and radiant temperature of 20.5 ± 0.03 °C. The average air speed in the occupied zone during all tests was maintained below 0.2 m/s.

The user control inputs for the heating personalized system during 14 sessions for two test subjects are shown in Figs. 6 and 7. The figures show the hourly distribution of average, maximum and minimum user settings of all 14 test sessions Subject A during all 14 sessions never used the heating in first 15 min. Subject B, the user never used heating in the first 46 min in any of the tests. After starting to use the heating, the setting increase during the test period and tend to stabilize towards the end of the test session. For subject B the highest heating setting used was 74% of the maximum. Test subject A for a brief moment used a heating setting of 83.5% of the maximum. The number of interactions with the slider per test was 2.6 ± 1.02 for subject A and 3.07 ± 1.03 for subject B.

3.2. Modeling results

3.2.1. Neural network NARX

Table 4 shows results of different networks with a varying number of hidden neurons for individual model A and B. Table 4 shows the network performance during training (MSE is taken as the network performance). A low MSE of the algorithm indicates good training. If the predicted values are very close to the true values the MSE will be small. In case that the predicted and true responses differ substantially, the MSE values will be large [64]. The values of MSE <0.001 are described as acceptable in [49], and in this study the models with values of MSE closer to 0 are considered to have good performance. Significant improvement in accuracy and performance was observed in models with a higher number of hidden neurons.

This initial assessment showed that for both test subjects, the individual neural network with a higher number of hidden nodes showed the best performance. One thing that should also be considered is overfitting. Fig. 8 shows performance plot of the neural network with 12 hidden neurons for the individual model A. Fig. 9 shows performance plot of the neural network with 16 hidden neurons for the individual model B. In the performance plot it can be seen at which iteration (epoch) the best validation performance was achieved and the training stops if the validation performance does not improve in 6 additional iterations. The sign of overfitting is that in the performance plot the test MSE increases significantly before the validation MSE increases. As it can be seen, both Figs. 8 and 9 do not show any major problems with the training since the validation and test curves are very similar. For all created network the performance plots were evaluated to ensure that overfitting did not occur.

The results of the evaluation of how the trained network predicts with the unseen data are shown in Table 4. The neural networks with lower performance (lower number of hidden neurons) showed lower ability to accurately predict with new unseen data. In the case of a model with a higher number of hidden neurons (10–18), RMSE values showed a good agreement between the measurements and the model predicted values for both models (A and B). The lower RMSE values (zero being the best possible result) the better agreement is between the real values and the model estimated values [65]. The best performances were shown for a neural network with 12 and 16 hidden neurons. In addition, the good prediction accuracy was confirmed with correlation coefficient PCC that was in these cases larger than 0.90. The Pearson correlation coefficient can result in values within the range [−1, 1]. Values close to zero demonstrate that there is no relationship between the predicted and the real numbers. The positive or negative rela-

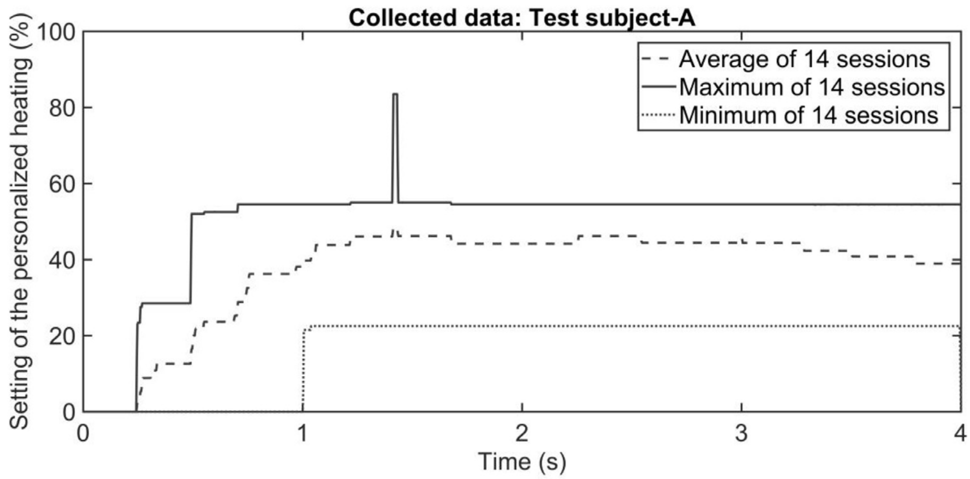

Fig. 6. Settings of the personalized heating system collected during 14 sessions (days) for test subject A.

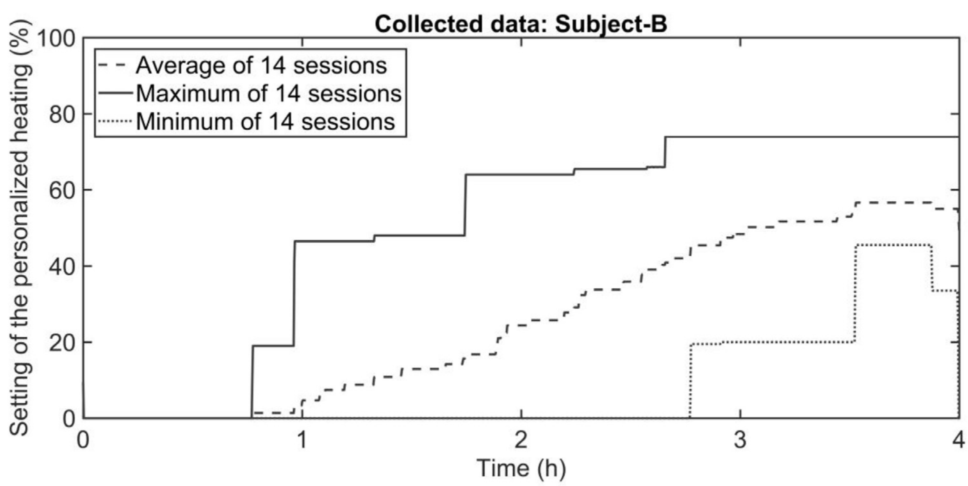

Fig. 7. Settings of the personalized heating system collected during 14 sessions (days) for test subject B.

Table 4
Performance of the created network with a different number of hidden neurons and the evaluation of the created networks to predict using the new unseen data for the test subject A and B.

Individual model A								
Performance of the trained network								
Hidden neurons	2	6	8	10	12	14	16	18
Network performance (MSE)	0.0138	0.0026	0.0011	0.0006	0.00029	0.00029	0.00028	0.00026
Evaluation of the trained network with the unseen data								
RMSE	0.326	0.096	0.148	0.057	0.043	0.071	0.060	0.078
PCC	0.889	0.972	0.946	0.986	0.994	0.986	0.991	0.983
Individual model B								
Performance of the trained network								
Hidden neurons	2	6	8	10	12	14	16	18
Network performance (MSE)	0.0148	0.0036	0.0018	0.0009	0.0004	0.0003	0.0002	0.0003
Evaluation of the trained network with the unseen data								
RMSE	0.335	0.299	0.242	0.240	0.082	0.118	0.049	0.092
PCC	0.855	0.877	0.920	0.922	0.990	0.982	0.996	0.989

tionship is defined with the sign of the correlation coefficient [66]. Values close to 1 present strong relationship in case of few pairs in data, and in case of a large amount of data pairs values closer to 0 can still be considered statistically significant [29]. It is stated in [37] that correlation coefficient values above 0.90 demonstrate a high level of prediction and acceptable quality of the results. In this study, the selection of the optimal models included the model that has PCC value closer to 1.

The high correlation coefficient in cases with networks with a higher number of hidden neurons for both individual models indicates that the developed predictive model is capable of describing the behavior of the targets with good accuracy.

For model A, the optimal network that provided the best results was the network with 12 hidden neurons with RMSE = 0.043 and PCC = 0.994. The best result for model B was obtained with

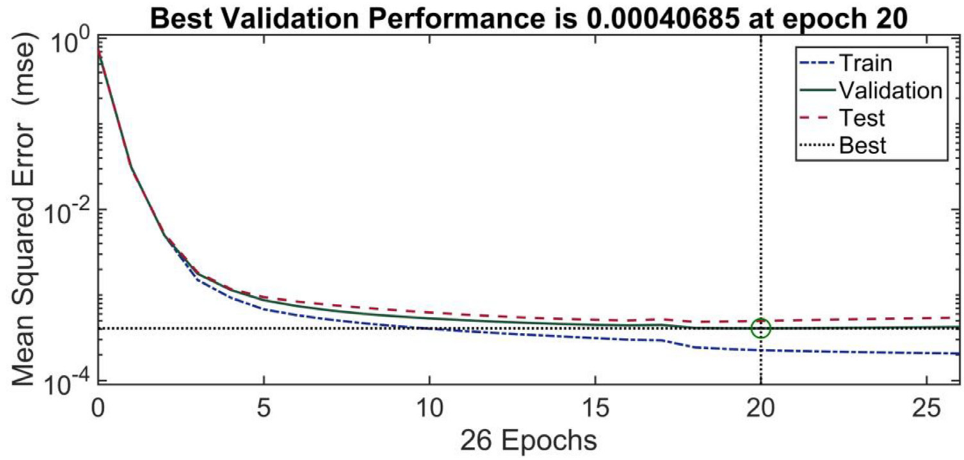

Fig. 8. Training performance of the neural network with 12 hidden neurons for individual model A.

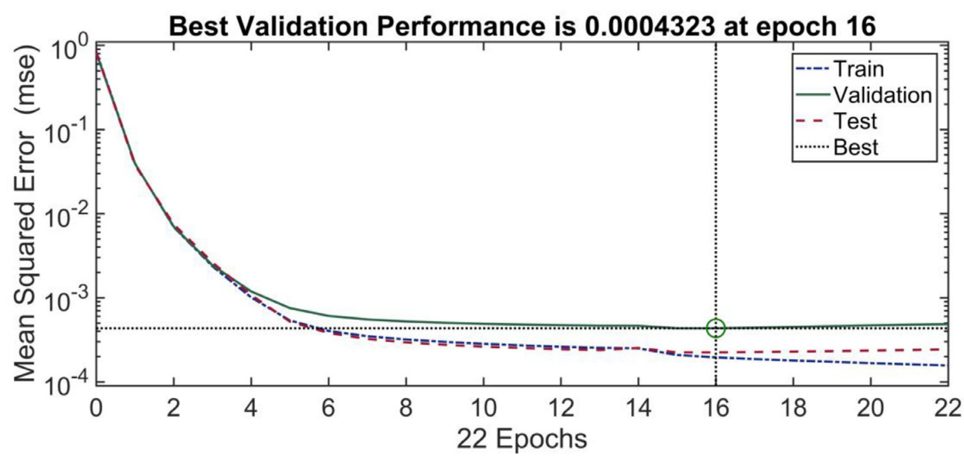

Fig. 9. Training performance of the neural network with 16 hidden neurons for individual model B.

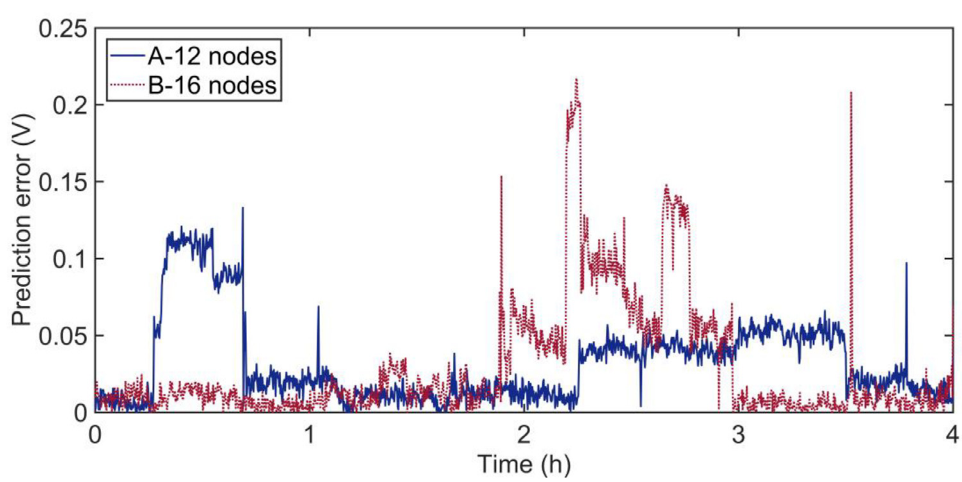

Fig. 10. Prediction error for the neural network model during the four-hour session for test subject A (model with 12 hidden nodes) and test subject B (model with 16 hidden nodes).

a neural network with 16 hidden neurons with RMSE = 0.049 and PCC = 0.966.

Fig. 10 represents absolute error between predictions and unseen data obtained with the best NARX model for test subject A and B. The NARX model for test subject A achieved a mean absolute error of 0.032 which corresponds to 1.6% of maximum value and for test subject B 0.029 which corresponds to 1.45% of maximum value, respectively.

The results of best correlation coefficient are shown in Fig. 11 and these values were comparable to the results in [26], where the correlation coefficient was equal to 0.997 (obtained with NARX model).

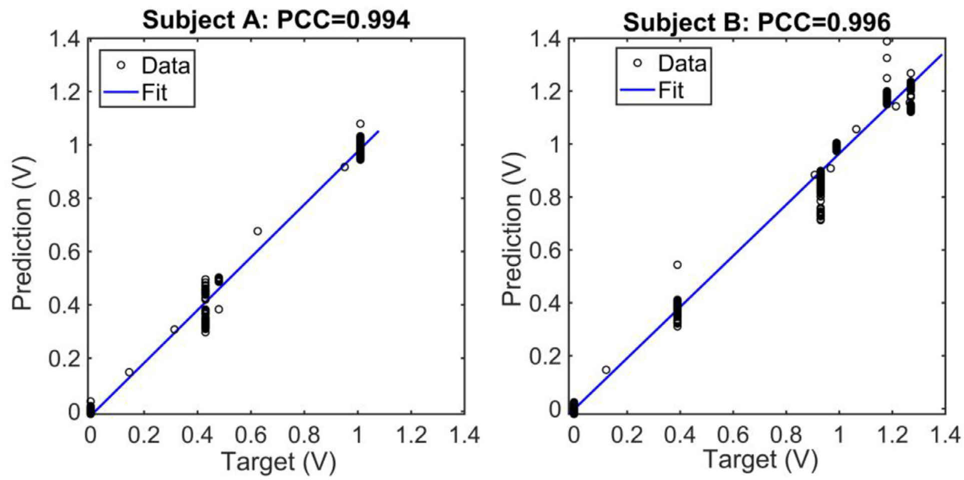

Fig. 11. A comparison between the unseen target data against the predicted personalized heating settings: left-test subject A model with 12 nodes and right-test subject B model with 16 nodes.

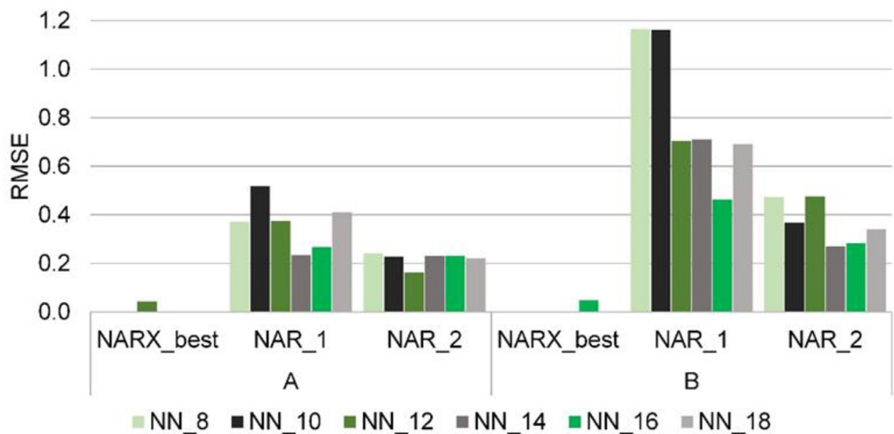

Fig. 12. RMSE values for three different models using the neural network with a different number of nodes.

3.2.2. Nonlinear autoregressive (NAR) network

The model that used NAR algorithm and averaged data of 10 s (NAR_1) showed average MSE for all tested architectures (number of hidden nodes) of 0.0005 for model A and 0.0006 for model B. In case of NAR algorithm with averaged data of 5 min (NAR_2) the averaged MSE calculated is 0.0116 for model A and 0.008 for model B. These values are slightly higher than the best values obtained with the NARX model. Fig. 12 shows RMSE values obtained with NAR_1 and NAR_2 models in comparison to the best values obtained with the NARX model for individual A and B. The RMSE values represent the prediction accuracy of the models with the new unseen data. For both individual models, NAR_2 results in average lower RMSE values obtained with the NAR_2 model. Furthermore, when compared to best results with NARX models for both individuals NARX network showed better results.

3.2.3. Regression techniques for machine learning

Table 5 summarizes all the results obtained with regression algorithms. The prediction accuracy of the models with the new unseen data is expressed with RMSE and PCC. The lower values of RMSE that evaluate the prediction accuracy and ability to predict with minimum average error show better performance. In case of the individual model A, the best performance was obtained with the SVR with the coarse Gaussian function with RMSE equal to 0.175. This result is still showing lower prediction abilities when compared with the best results obtained with NARX. Gaussian process regression with Matern 5/2 kernel function showed the best performance with RMSE equal to 0.319 for model B. However, compared to the best results obtained with the NARX model it is showing lower performance.

3.3. On-line implementation results

During the on-line tests, the indoor environment had an average air temperature of 20.1 ± 0.08 °C, relative humidity of $36 \pm 1.4\%$ and radiant temperature of 20.2 ± 0.09 °C. The average air speed in the occupied zone during all tests was maintained under 0.2 m/s.

As mentioned, there were six tests for each test subject where in three tests it was automatic control and in three the test subject could overwrite the automatic control if the preferred different setting. Both test subjects did not overwrite the predicted settings at any moment of the test. Not interfering with the predicted settings was also reflected in the thermal comfort votes. Average overall thermal comfort over the whole session is shown in Fig. 13. It can be seen that in both modes of control both test subjects felt comfortable throughout the test. There was a slight increase in comfort in tests with predictive control. For subject B average overall comfort votes were 3.86 ± 0.49 in user control mode and 4.88 ± 0.22 in predictive control mode. Average overall comfort votes of subject A were 0.91 ± 0.33 in user control mode and 1.77 ± 0.45 in predictive

Table 5
Performance of the models using regression algorithms.

	Individual model A			Individual model B		
Regression algorithm	Network performance	The performance with the unseen data		Network performance	The performance with the unseen data	
	MSE	RMSE	PCC	MSE	RMSE	PCC
SVR-FG	0.02	0.336	0.604	0.02	0.394	0.613
SVR-MG	0.02	0.334	0.687	0.03	0.340	0.767
SVR-CG	0.06	0.175	0.865	0.08	0.362	0.817
Bagged trees	0.01	0.286	0.737	0.01	0.334	0.809
Boosted trees	0.03	0.221	0.858	0.03	0.445	0.717
GPR-E	0.02	0.320	0.670	0.06	0.327	0.803
GPR-M	0.01	0.318	0.693	0.02	0.319	0.798
GPR-SQ	0.02	0.308	0.746	0.02	0.328	0.773
GPR-RQ	0.01	0.304	0.740	0.01	0.323	0.805

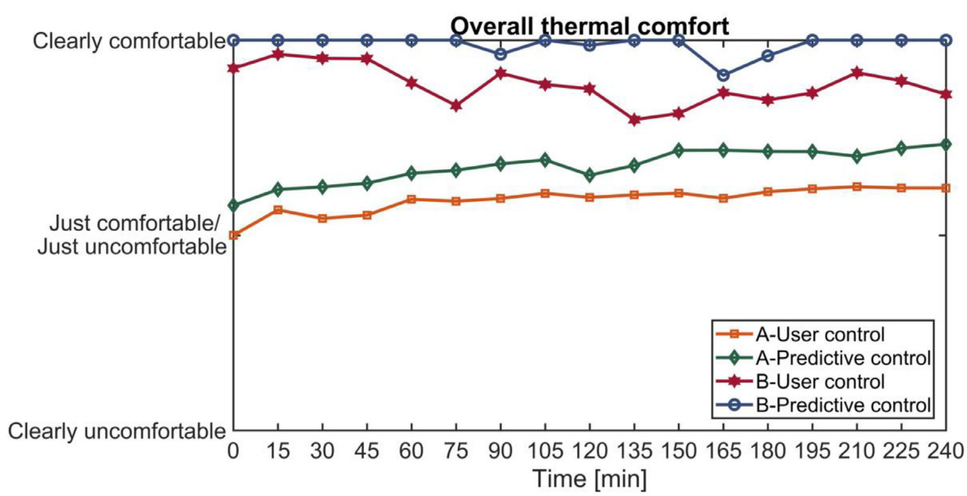

Fig. 13. Average overall thermal comfort over the whole session.

control mode. This suggests that the user control and predicted control provided the same level of thermal comfort under given environmental conditions.

The same trend was seen in local thermal comfort, where the increase can be seen in local comfort votes between control modes in both test subject. The local thermal comfort of the head, the back, the hands, and the feet after 1 h and at the end of the session are shown in Fig. 14. Both control modes provided a similar level of comfort for each subject, with a slight increase in comfort vote on a scale in favor of predictive control mode for every investigated body part.

User control settings of fourteen sessions and predicted settings during predictive control mode are shown in Fig. 15. The predicted settings during tests with subject A increased at the beginning of the session and tended to stabilize from the middle of the test towards the end of the test session. The predicted settings had only for a brief moment after 75 min of the test a higher value of 1% of maximum possible setting than the maximum value in the user control tests. The predicted settings of subject B increased during the whole session, but remained in the same range as the user controlled settings except during six minutes in the third hour of the session when the predicted value went slightly below the minimum (less than 1% of difference) of tests with user control settings.

In the test cases, when personalized heating was user controlled, the settings remained stable over the last 30 min of the session. Energy consumption of the personalized chair is shown in Fig. 16. The two tested control modes for subject A sessions showed average energy consumption of 22.8 ± 8.7 Wh in user control mode and 25.8 ± 2.3 Wh in predictive control mode. The average energy consumption of subject B sessions was 15.8 ± 10.1 Wh in user control mode and 13.2 ± 0.9 Wh in predictive control mode.

It is important to mention that the test subjects expressed their satisfaction with automatic control and commented that their self-evaluated performance was higher in the tests with automatic control in comparison with the user control. They expressed they could focus more on their work tasks.

4. Discussion

Artificial neural network is a powerful data-driven method that is able to deal with linear and nonlinear characteristics. However, the limitation of black box models is that the user cannot interpret the physical meaning and to know how learning from input data was performed. The main advantage of the models is that it is learning individual settings, therefore the gender, age or BMI are implicitly included in the model since each predictive model was trained using data collected from a specific person. The model inputs at the moment only include environmental data, and the information on clothing and activity level (metabolic rate) that also influence thermal state is not included as an input but was taken as a fixed condition. In the performed experiment the test subjects were wearing clothing of similar insulation grade during all sessions and were performing their usual office activities. In a normal office environment, it is expected that the people maintain a similar clothing level during the heating season and perform sim-

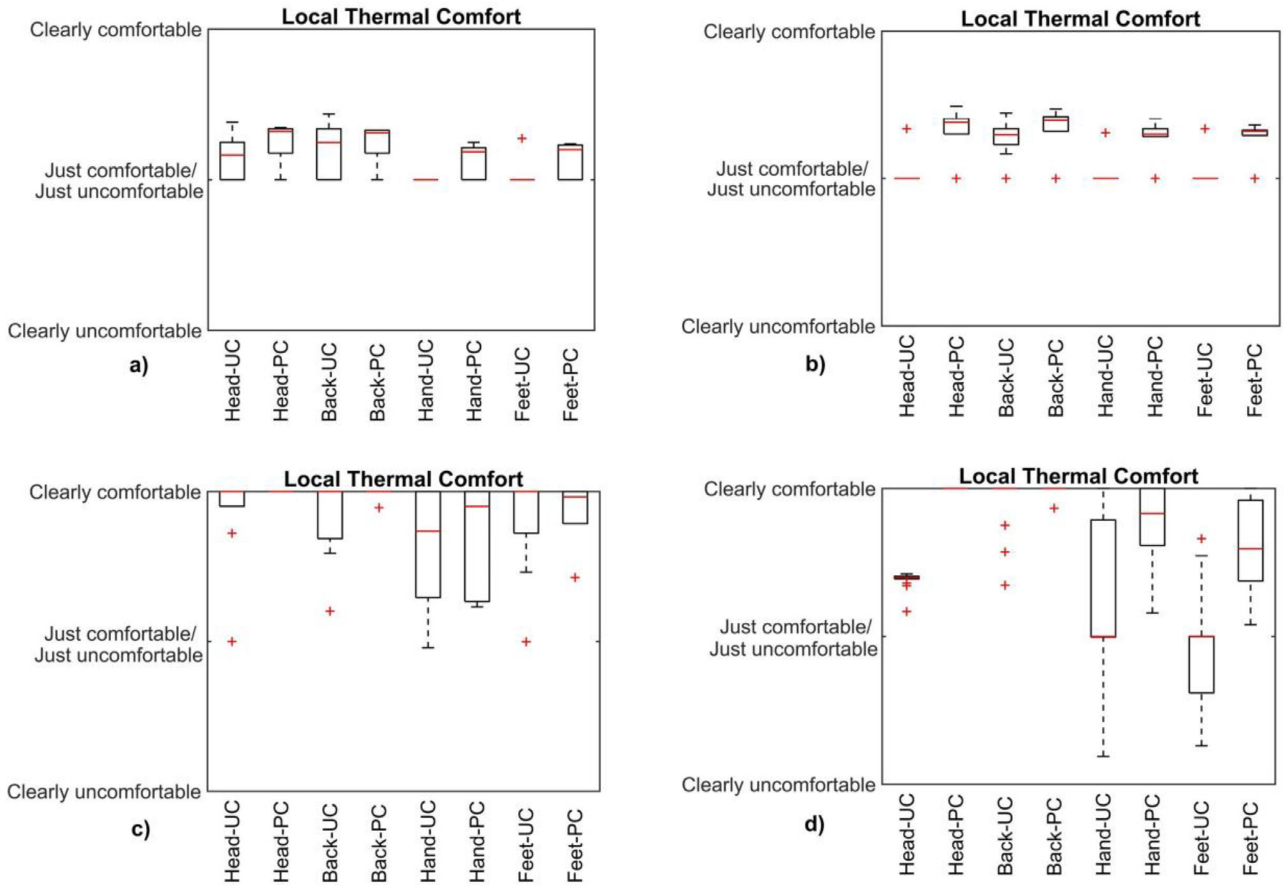

Fig. 14. Local thermal comfort during user control (UC) and predictive control (PC): (a) for subject A after 1 h, (b) for subject A at the end of the session, (c) for subject B after 1 h, (d) for subject B at the end of the session.

ilar activities. Furthermore, the used inputs are considered in the model for practical reasons and on-line implementation in a real office environment as they are easily implemented in climate control systems.

The approach of multiple tests for each subject instead of a large number of subjects that participate in a single test was done to be able to create a specific individual model, not a model for the average person. The personalized model is used for personal control of the personalized heating system and is a necessary step before considering multi-person modeling. The first step in this methodology is to be able to predict settings of each individual. Based on this method if we have more people sitting in the open office space in their permanent spot, their individual models can be created by collecting the data in the first few days when they use their personalized conditioning system. The next step would be developing grey-box models that could be used for multi-person cases that would be categorized by their physiological differences as age, BMI, gender. In addition, with the future development of the wearable sensor, skin temperature could be used as a real-time input for the predictive model.

Keeping in mind that more experiment is needed, the impact of a number of training data sets was also investigated by training the models in order to see if the size of the dataset could be reduced that would reduce the time and resources for collecting the data. The training was done with 3, 5 and 8 sessions. It was found that all model training with three and five sessions of data and different architecture often resulted in signs of overfitting in the performance plots. This was expected because a small dataset has higher possibility to result in overfitting. We also found that the results with the eight days dataset resulted in the similar trend as training with thirteen sessions dataset (average RMSE = 0.067 and PCC = 0.982 for model A; average RMSE = 0.099 and PCC = 0.979). This could be helpful when performing future experiments for different individuals and would ensure a shorter period of data collecting. As overfitting can be serious issue in case of limited amount or missing data there are few approaches that can be taken. The best case scenario is to get more data if possible for each individual. The other steps that can be taken is to test the generalization of different algorithms (different models) and its ability to handle unseen data. In this study, several algorithms were tested with the unseen data and the performance of each was compared. Other step that could be considered in cases with limited data as presented in Jin et al. [67] is to adopt other machine learning techniques such as transfer learning.

There are limitations in this study that should be noted for future work. The first limitation is that the tests were performed in a uniform thermal environment. In the real office, indoor conditions vary more during the day. Unlike the HVAC system that aims to create a uniform environment in the whole space for a large group, PCS aims to condition the space around individual occupants by exposing them to non-uniform and non-steady-state conditions [13,68]. This leads to a necessity to research comfort under the effect of combined methods of conditioning [68]. There is a lack of studies that are predicting settings of personalized heating systems, and to our knowledge, there are no studies with implementing their predictive models into automatic control. Therefore, the approach of testing this methodology in a more controlled environment in a climate chamber was determined as a first step. This approach gave us information how the preferable heating settings for each test subject changed with time even though the in-

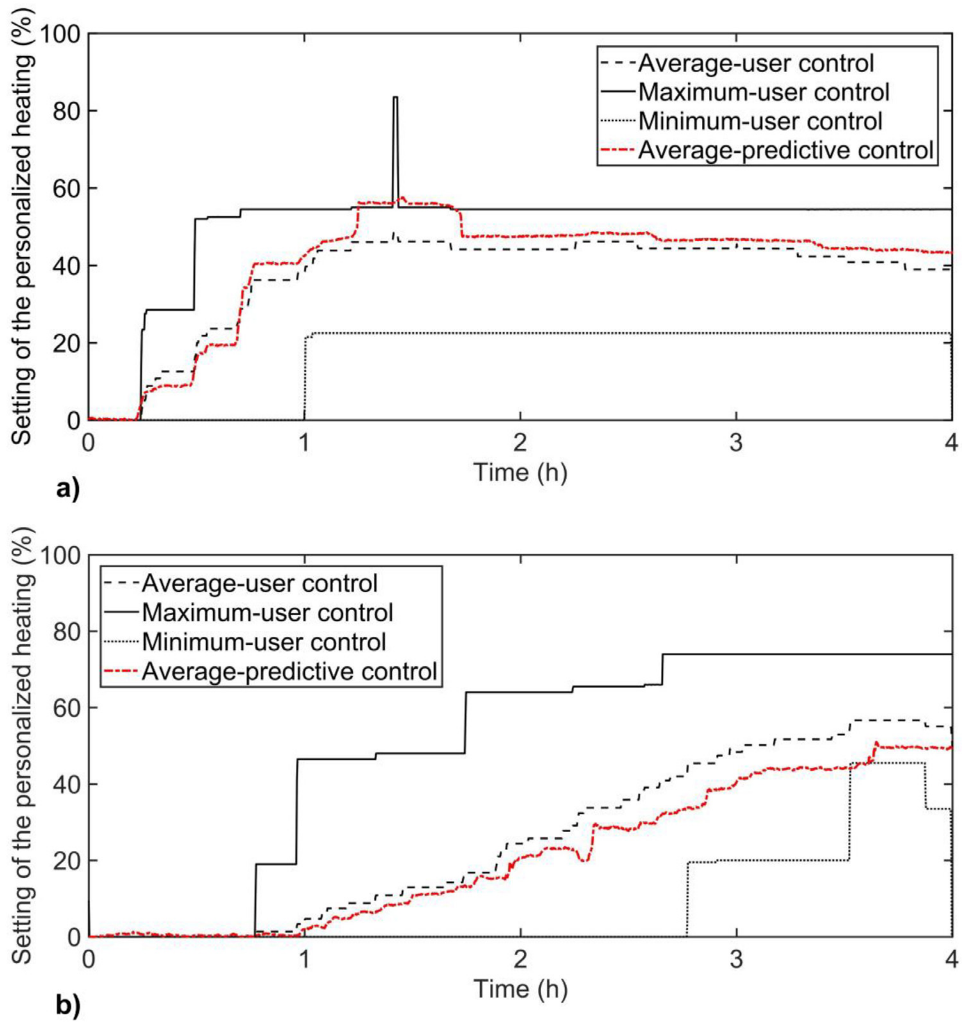

Fig. 15. User control and predicted settings for (a) subject A and (b) subject B.

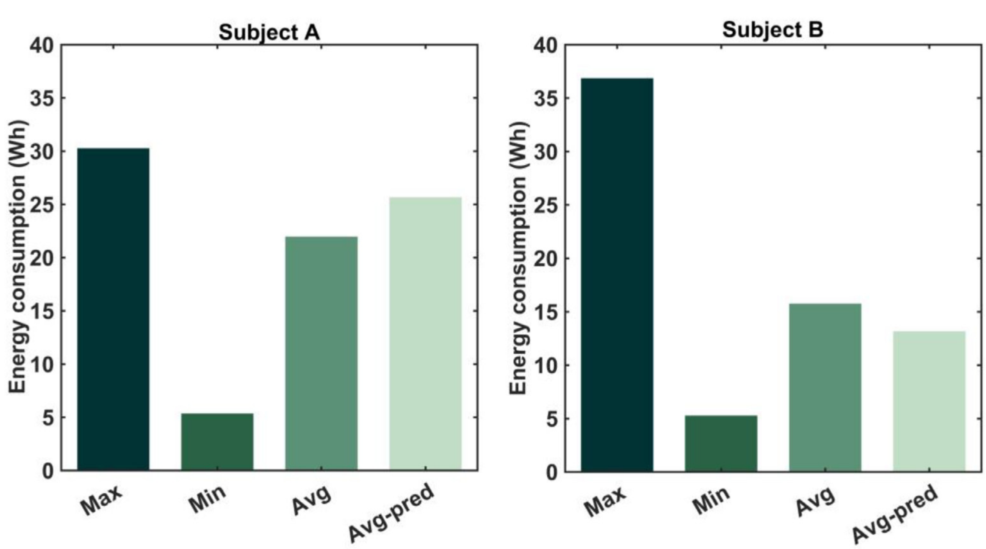

Fig. 16. Maximum, minimum and average consumption during user control and average energy consumption during predictive control.

door conditions did not change. One of the main aims was to test if the user interaction can be substituted with the predictive control. The results of comfort feedback of the occupants showed it can, however, it has to be noted that the test presented in this study were performed only at ± 20 °C air temperature. For future work, it is recommended to further investigate and test over a wider range of environmental conditions including the transient conditions during the testing day. The other limitation is size of the tested occupants. This study presents the whole procedure of collecting the data, developing the predictive models and implementing the models in the automatic control. The focus is on individual models and not a model for an average person. We recommend testing more people in a field study where it is possible to test more subject at the same time. The climate chamber study has the advantage of greater control of irrelevant variables, however testing multiple test subjects takes more time. The results that are obtained in a controlled experiments in a climate chamber result in new approaches and methodologies that should be investigated in the field. As Parsons [69] noted, climate chamber experiments and field studies should complement to each other. Furthermore, on-line learning in the real office that can capture new patterns in the data and update the model should be considered as future research.

5. Conclusion

In this paper, we demonstrated how to use machine learning can be successfully used for the control of personalized heating systems. Individual predictive models were developed using artificial neural network algorithm and validated with the offline analysis and the on-line implementation. Neural networks were trained and tested using collected data from two individuals. Data was collected during four-hour experiments for 14 days in a mild cool environment. NARXs were created that represent individual models for each test subject. The neural network was trained with Levenberg–Marquardt back-propagation algorithm and various architectures were tested. The analysis showed that the networks with a higher number of hidden neurons (10–18) have better performance. The predictability of the developed models was evaluated with new unseen data. For test subject A the best results were obtained with a neural network with 12 hidden neurons: RMSE = 0.043 and PCC = 0.994. For test subject B, the best results were yielded with a neural network with 16 nodes: RMSE = 0.049 and PCC = 0.996. These models were then used in the on-line implementation where extra six tests were performed for both test subjects. In addition, other algorithms were tested including NAR and regression algorithms (SVR, GPR, Bagged and Boosted trees). Even though the performance of these models tested with the unseen data were satisfying, the best results obtained with NARX model showed unmatched performance. Among all algorithms, it was noticed that Gaussian process regression requires the most time to finish the training process.

The first contribution of this study is the demonstration of using learning algorithms to directly predict individual settings of the heating chair. The second contribution is the implementation of predictive models in automatic control of the heating chair and the online testing. The model validation and the on-line implementation showed that the developed predictive models are accurate to predict individual setting of the personalized heating system and the model can provide a quality substitute for user's control. The predictive control provided a slightly better level of thermal comfort and resulted in similar power consumption when compared to user control. Furthermore, it is important to emphasize that these individual predictive models are valid for environmental conditions similar to the test conditions.

Declarations of interest

None.

Acknowledgments

The research is partly funded by the EuroTech Universities Alliance. Further financial support was given by the professional foundation PIT and the educational organization OTIB. We also would like to express our acknowledgment to Elena Mocanu for her advice concerning machine learning.

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