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Model Predictive Control for Preventive Conservation using Artificial Neural Networks

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Abstract

In applications of preventive conservation the main goal is to achieve an indoor climate fitted for the conservation of cultural heritage. The appropriate range for the indoor climate is hereby given by the specific materials which shall be conserved. Especially inside historic buildings the area to install HVAC systems is restricted due to the exhibited cultural heritage. The use of state of the art bang-bang controllers in HVAC actuators often leads to undesirable climate fluctuations which are causing damage to cultural assets. A studied approach to enhance the indoor climate behavior is the usage of model predictive controllers (MPC), which are able to plan future control actions. Therefore a weather forecast is needed to compute future climate states, whereby the accuracy influences the outcome of the model prediction. In addition, an appropriate model for the climate behavior of the building has to be developed, which turns out to be a challenging task.

In this paper we present a MPC using an artificial neural network (ANN) as a process model. Since the network structure of ANN determines the function approximation capabilities, a process called neuroevolution is used to fuse learning and constructing of the ANN structure. Also an ANN model is used to enhance the weather forecast by adapting it to local influences. To conclude our work, we simulate the proposed controller with real measurement data acquired from castle "Schloss Fasanerie".

Keywords - Preventive Conservation; Model predictive control; Black box modelling; HVAC control

1. Introduction

The main task of preventive conservation deals with the preservation of cultural heritage by reducing damages caused by inappropriate indoor climate. To avoid damages, acceptable ranges for temperature, humidity and air pollution for different materials are suggested (see [1]). Further, short term fluctuations of temperature and humidity lead to energy and mass transports which stress the materials and should be avoided.

Making explicit statements for such ranges is difficult. A low humidity in combination with high temperatures may lead to dryness in objects and high humidity provokes biological issues like mold or sponge. Furthermore, changes in temperature and humidity in addition with sorption effects cause physical damages (see [2]). Therefore an elaborate control strategy, which is designed in respect to fluctuations and acceptable ranges, should be considered. State of the art systems, like mobile air conditioners, often use bang-bang controllers which will lead to additional fluctuations.

To develop a control strategy which may reduce the mentioned effects, a preferably accurate model of the climate behavior of the room is needed. This is necessary to predict the future climate behavior and to plan the control actions. The behavior of the regarded room mostly depends on material properties and is strongly linked to the outdoor climate. With a variety of materials and different properties, a lot of information would be needed to construct an appropriate model. Another approach may be the use of measurement data to build a data driven (black box) model.

The real world application investigated in this paper is castle "Schloss Fasanerie", which is a well-studied application in different projects (see [3] and [4]). It is a typical object for preventive conservation, because the castle is used as a museum during the summer months with the interest to preserve the variety of exhibition objects of different age, origin and epochs. Typical problems for those applications are given by the old building stock and the hereby linked bad isolation and storage effects. Also the building stock limits the usage of HVAC systems, due to the preservation of the building. Nevertheless, in this application climate data has been logged for several years and different models for simulation have been developed. Also the data is used for constructing and validating the needed models and control strategies.

To build a model predictive controller (MPC) (see [5] for details), a model for the prediction of future climate states is essential. While a local weather forecast for the location of the mentioned application would be suitable, only a forecast regarding the nearby region is available, which leads to a significant lack in accuracy. Hence an approach for the local adaptation should be brought up.

Artificial neural networks (ANN) are used in this paper, since the variety of model structures is useful for creating a local weather adaptation as well as a building behavior model. Furthermore a neuroevolution approach, as presented in [6], combines constructing network topologies with data driven learning to find an optimal network in order to represent the systems behavior.

2. Neuroevolution for Artificial Neural Network

Using a network of artificial neurons for learning system behavior is driven by the idea of imitating biological neural networks, which are essential for learning processes in the brain. An artificial neuron itself has a number of weighted inputs and one output. The activation of the output is computed by an underlying activation function. If the inputs of the neuron exceed a certain threshold, the output fires according to the used function. Different functions may be represented by constructing networks. Especially in the mentioned application the storage of energy and humidity is an essential part of the climate behavior. This can be described by using recursive connections in a network structure to reach better approximation capabilities. Unfortunately, these recursive connections lead also to a higher complexity. For further and detailed information on the principle of ANN see [7].

2.1 Neuroevolution

In order to find an appropriate network structure and weighting coefficients of a neural network, evolutionary algorithms may be used. This can be done by transferring the network structure and weighting coefficients of a designated ANN in an artificial gene sequence and using these genes as individuals of a population. Different approaches are available for tackling this task but the usage of an adapted NEAT algorithm (see [6]) seems to be the most beneficial. To code the network into a gene structure, the main attributes (weightings and connection) have to be available. Also to distinguish network structures and to prevent its repeated usage, an innovation number is used, based on the connections of a neuron (see Fig. 1). If a connection is not present in a structure, it is simply disabled and the sequence is preserved, so the gene sequence marked by the innovation number is still available.

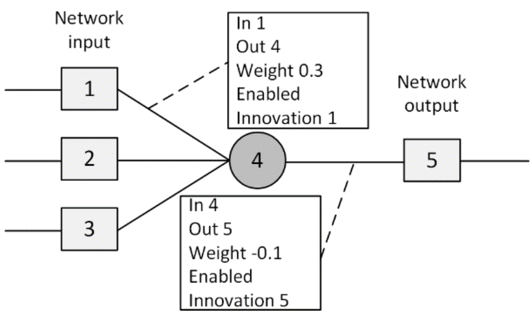

Fig. 1 Stucture and Gene coding of the first generation of an ANN

2.2 Evolutionary component

The evolutionary component is now used by the recombination, mutation and selection of different individuals. First of all a population of different individuals is set up by using a simple network structure with one neuron, various weights and different enabled connections to the inputs and outputs (as to see in Fig. 1). After a population is given, the fitness of every individual is determined. The fitness of each individual is the ability to meet the wanted function (building model or local weather adaptation). Here the normalized mean square error (NMSE) with predicted output $\hat{y}_i$ and measured output y_i (here temperature or humidity) is used for instance for temperature.

$$\mathrm{NMSE} = \frac{\sum_{i=1}^{N}(y_i -)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{1}$$

To select the best individuals for recombination, a shared fitness function is used. So, the survival of an individual is determined by its fitness in perspective to the fitness of the other individuals. The relative error $e_{rel}(i)$ of individual i is set in respect to the global absolute population error, as shown in (2).

$$\mathrm{e}_{rel} = \frac{e_{abs}(i)}{\sum_{n=1}^{pop} e_{abs}(n)} \tag{2}$$

If a new innovation emerges by mutation, the new individual will most likely be not very successful in solving the problem. To protect those innovations, similar individuals are grouped into species. Those species share a relative error within their niche and not with the entire population, so they are just in competition with their own species. To find organisms of one species, a distance δ (as shown in [6]) of the similarity of genes is calculated by the linear combination of the number of excess E and disjoint D genes, as well as the average weight differences of matching genes W, including disabled genes. To adjust the normalized genes, the number of all genes N is used and a weighting of the importance is done by c_1, c_2 and c_3 see (3):

$$\delta = \frac{c_1 E}{N} + \frac{c_2 D}{N} + c_3 W \tag{3}$$

After determining the species, the selection within a species can take place according to the probability depending on its relative error. Then two individuals are selected, their genes (determined by the innovation number) are recombined randomly with the genetic feature of one parent or a combination of both features. Afterwards a new individual is formed. By chance a mutation, which could be a new gene sequence or the changing of an already existing one, may appear. At last, species and fitness of the new individual will be ascertained. If the new individual has a better fitness then the worst individual within its niche, it will replace the worse one. If there is no other species within its niche (so this is a new species), the worst individual of the biggest niche is replaced. This process is illustrated in Fig. 2.

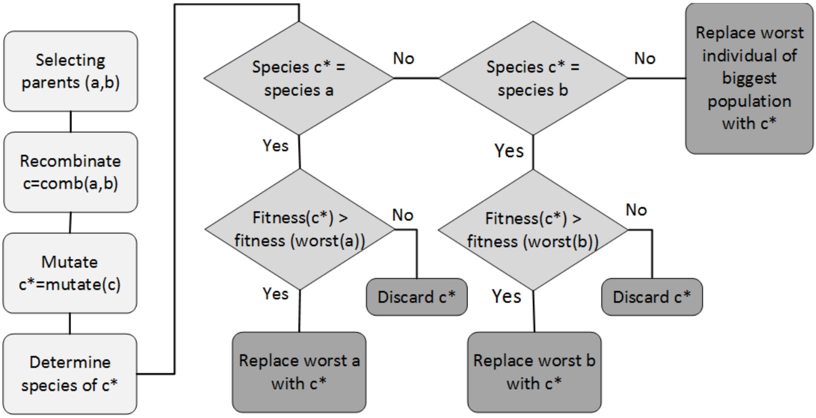

Fig 2. Flowchart on creating new individuals within a population

3. Building of Model Predictice Controller

To use an MPC for reducing the above mentioned fluctuations, the local adaptation of the weather forecast is required, because this adaptation is utilized for the learning of the building model. As described in [8] this usage is appropriate for an MPC.

Separating the two tasks of predicting temperature and humidity helps to reduce the network complexities for the weather forecast as well as for the building model.

First of all, the prediction horizon has to be determined to a size, where future changes in temperature and humidity have significant influence on the trajectory planning for a controller. Therefore the coupling of the room with the outdoor climate and the precision of the weather forecast is considered.

3.1 Local weather adaptation

The weather forecast used here was acquired by a commercial weather service, which provides a forecast up to 5 days in 3h prediction steps and is updated every hour. To determine the accuracy relating to the local weather of the location of the application, the forecasts of half a year were logged, while the local climate was measured by a weather station.

The rate of the absolute errors E (see eq. (4)) of the forecasts are shown for a horizon up to 24h in Fig. 3, thus a further extension of the horizon would not be able to enhance the control quality, due to the efficiency of actuators and the coupling of indoor and outdoor climate. Considering the increasing error over time and the planning of control variables, the prediction horizon is chosen to be 9h.

$$E = y_{measured} - y_{predicted} \tag{4}$$

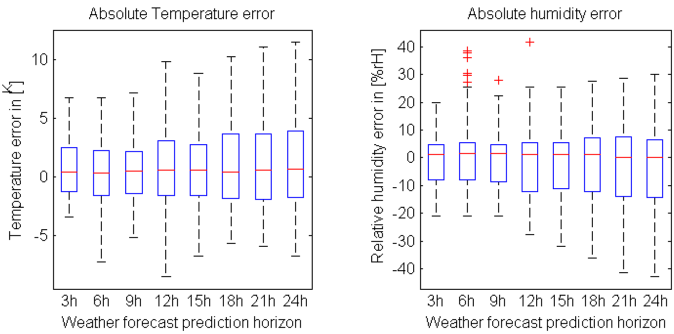

Fig. 3 Absolute temperature and humidity error of weather forecast with horizons between 3h and 24h

To build up the model using neuroevolution, inputs and outputs for the ANN have to be determined. Temperature and humidity are separated in two different ANN models in order to reduce model complexity. To determine the needed inputs the quality of the prediction of different ANN is compared by the NMSE (see eq. (1)). The current value of temperature and humidity and a variation of past values, as well as the prediction for up to 9 hours were chosen as inputs. The outputs are defined as the desired adapted forecast for up to 9 hours (in 3 hour steps). In table 1 the different errors for the ANNs, with the number of past measured values in 15 min steps, are shown in perspective to the original forecast.

Table 1. Error in predicting temperature with different ANNs with number of past inputs

NMSE	3h	6h	9h
original	0.0953	0.1068	0.0964
ANN(1)	0.0886	0.0755	0.0819
ANN(2)	0.058	0.0774	0.0795
ANN(3)	0.0556	0.0681	0.0714
ANN(4)	0.0511	0.0623	0.0691
ANN(5)	0.0521	0.0614	0.0633

Since the accuracy doesn’t increase in a reliable perspective to the growing complexity with more inputs, the ANN with 4 inputs is chosen as local adaptation model. The ANN structure determined by neuroevolution contains 6 Neurons in 2 layers and no recurrent connections.

The ANN model for humidity was also determined with 4 past inputs. The yielding errors are shown in Table 2. The resulting network structure determined by neuroevolution contained 5 Neurons in 2 layers and no recurrent connections.

Table 2. Error in predicting humidity

NMSE	3h	6h	9h
original	0.1205	0.1624	0.1670
ANN(4)	0.0592	0.0585	0.0695

3.2 Building Model

In order to build a model for the climate behavior of the building, a simulation model which was accomplished in previous works for the simulation program TRNSYS (see [4]) is used, since the MPC using this model is also tested on this simulation. The building of a model only using measured data (without simulation) and the importance of recurrent network connections is shown in [9].

The time steps of the building model were chosen at 15 min with respect to control variable planning of the MPC. The weather forecast itself is only updated every hour, so a linear interpolation between the different adapted forecasts is done. A further adaptation is done by the model itself while training the climate behavior. Additionally the coupling between the inside and the outside climate shows a kind of damping effect, so the impact of outliers in the prediction is reduced. As to see in Fig. 4, temperature as well as humidity model are trained with the same inputs. Those are the measured data of the outside climate and its past 5 values (timestep 15 min) as well as the adapted local weather forecast. The target function to reproduce is given by the simulation, in respect to the control variables of the heating and ventilation system. The created dataset of the simulation consists of the same climate data, once without and once with different combinations of actuator usage.

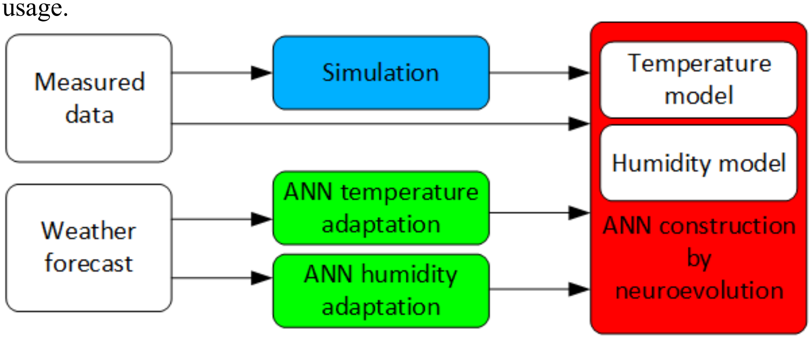

Fig. 4 Signals for construting an ANN building model

The temperature model was able to meet the 9h prediction horizon with a NMSE of 0.0315 and the humidity model with a NMSE of 0.0386. The better accuracy in aspect to the adapted weather forecast results by the damping behavior and the additional influence of the heating and ventilating system.

3.3 Model predictive controller using ANNs

The principle of an MPC is rather simple. The upcoming control actions are planned ahead by using a model. The planning considers a target trajectory regarding the predicted climate behavior. Evaluating a cost function offers the optimal control mode. If a reversible model for the process is present, the control actions may be calculated directly and an optimizer can solve a linear optimization problem, fulfilling the underlying cost function. In the case of not invertible models like ANNs a nonlinear optimization problem is present and must be solved (see [5]).

The cost function uses the deviation of the predicted temperature ϑ_i to the optimal temperature ϑ_s (for this application 20°C) and the deviation of the predicted humidity φ_i of the optimal humidity φ_s (for this application 50%rH) weighted in perspective to all goals with the factors $w_{\vartheta 1}$ and $w_{\varphi 1}$. The reduction of fluctuations is accomplished by considering changes in temperature $\Delta\vartheta_i$ and humidity $\Delta\varphi_i$ weighted with $w_{\vartheta 2}$ and $w_{\varphi 2}$. The summation over the prediction horizon N results in:

$$J = \sum_{i=1}^{N} w_{\vartheta 1}(\vartheta_s - \vartheta_i)^2 + \sum_{i=1}^{N} w_{\varphi 1}(\varphi_s - \varphi_i)^2 + \sum_{i=1}^{N} w_{\vartheta 2}\Delta{\vartheta_i}^2 + \sum_{i=1}^{N} w_{\varphi 2}\Delta{\varphi_i}^2 \tag{5}$$

To find the optimal control variable trajectory a differential evolution algorithm (see [10]) is used to build up the optimizer of the MPC as shown in fig 5. The MPC computes a control variable trajectory in 15 minute steps for 8 hours. By doing so exceeding the prediction horizon of the forecast is avoided. Only the first step of the control trajectory will take action. After 15 minutes the next trajectory is computed.

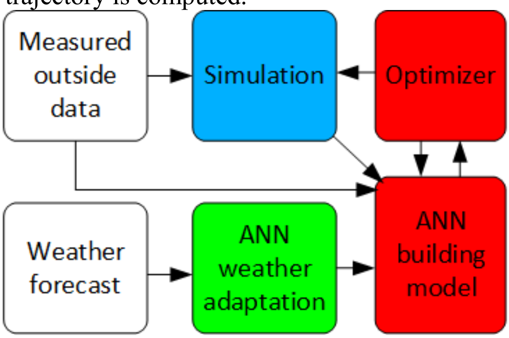

Fig. 5 MPC using ANN building model

4. Results

The simulation using the MPC is compared to the results of bang-bang controllers with a sampling time of 5 minutes for humidity and temperature.

Especially the ventilation device is not a continuous actuator, so the optimized control variable of the MPC has to be transferred to a pulse-width modulation. To do so, the ventilation is used for the fraction of 15 minutes that represents the degree of operation.

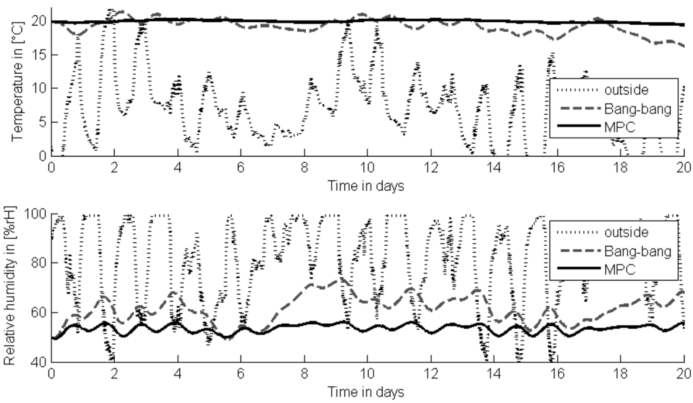

Fig. 6 Temperature and humidity by simulation using a bang-bang controller and a MPC

The simulation was done for a time span of 6 months. In Fig. 6 the history for the simulation of 20 days for temperature and humidity for the two control types is shown. The bang-bang controller was able to keep the temperature near the acceptable range but produces a high amount of short time fluctuations. Moreover the humidity shows also higher deviations additional to the higher fluctuations.

To interpret the fluctuations the amplitude spectrum for both controllers is shown in Fig. 7, which shows rate of frequencies. As to see, the MPC reduces high frequency fluctuations in temperature and reduces the fluctuations in humidity over the whole spectrum.

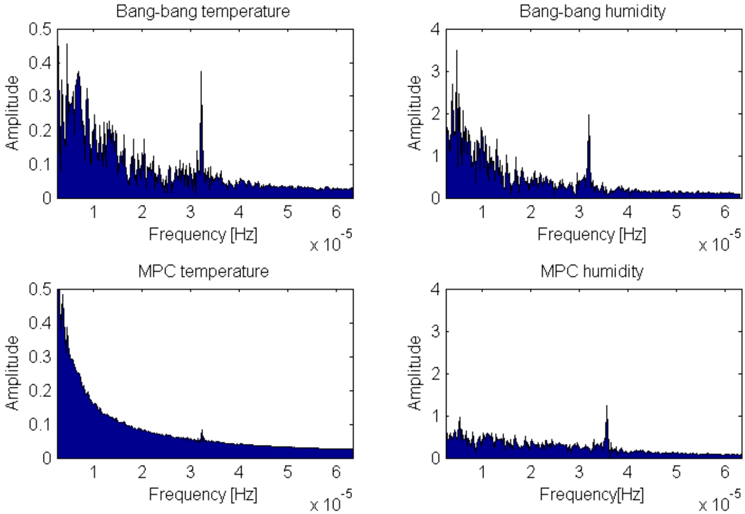

Fig. 7 Amplitude spectrum for tempreature and humidity

5. Conclusion and discussion

In this paper we presented the usage of an MPC in connection with an internal model represented by an ANN. This combination is able to reduce fluctuations in temperature and humidity compared to the use of bang-bang controllers, even if only non-continuous actuators are available. The usage of ANNs to improve a weather forecast to a local component was also presented.

The constructing of ANN structures using neuroevolution reduces the need of expert knowledge on ANN structures. The adaptation of the model depends on a sufficient amount of data, which is depending on the complexity of the function to reproduce. If the modelling effort for a building already was invested, the additional training of an ANN is not reasonable.

By adjusting the target function of the MPC, the goals of the controller may be adjusted to the applications needs, e.g. reducing fluctuations or actuator usage. By planning the control variables with respect to this needs and future climate states, these goals are accomplished. The solving of the nonlinear optimization problem is a task with high computing costs and computing time. For applications with faster processes this approach may not be applicable.

In future works the possibility to train an ANN for the adaptation of the optimal control variables computed by the optimization may reduce the computing effort.

Acknowledgement

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