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Design and construction of a non-linear model predictive controller for building's cooling system



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ABSTRACT

This research aims to optimize a multi-zone Air Handling Unit's (AHU) energy consumption by using a Nonlinear Model Predictive Control (NMPC) approach. In this paper, Genetic Algorithm (GA) and Non-linear autoregressive network with exogenous inputs (NARX) have been utilized to design NMPC for a multi-zone AHU. The NMPC problem could be divided into two main sections: internal model and the optimizer. NARX serves as the controller's internal model to predict the building's thermal dynamics. GA is then used to solve the NMPC problem and find the optimal value of the control signals at each time step. The proposed NMPC jointly minimizes energy consumption of the AHU and the deviation from the set-point temperature. Finally, the designed controller was implemented and applied to the mentioned AHU. Also, a data acquisition system has been fabricated to secure training and test data for NARX. Utilizing NARX for modeling system's dynamics resulted in a highly accurate model with an accuracy of 97.71%. The empirical results of the proposed NMPC showed significant reduction in gas and electricity consumption of the AHU. NMPC yielded a 55.1% and 43.7% reduction in electricity and gas consumption of the AHU respectively.

1. Introduction

Considering the increasing importance of energy conservation in recent decades, various methods and technologies have been developed to improve different energy systems. Building section is responsible for almost 40% of the global final energy use and 40% of greenhouse gas emissions in the United States of America [1,2]. Taking into account the huge contribution of Heating, Ventilation and Air Conditioning (HVAC) systems in a building's energy use, optimizing these systems could have a substantial effect on a building's energy consumption. HVAC systems account for 50% of the building sector's energy consumption [3]. Hence, optimizing these systems is both economically and environmentally beneficial. HVAC systems are employed to provide thermal comfort for the occupants in buildings.

To control HVAC systems, many control strategies have been proposed. The most common controllers applied to HVAC systems are PID (Proportional-Integral-Derivative), PI and on/off controllers. These controllers use current thermal parameters to generate control signals. But, since buildings have a very slow thermal dynamic, a large amount of energy is wasted in the control process. It has been shown that model predictive control is the best approach towards controlling building's HVAC system [4]. MPC utilizes a model of the plant to predict the future outputs or states of the system, and then it generates a control vector that minimizes a certain objective function over a control horizon [5]. Model Predictive Controller (MPC) is suitable for controlling thermal behavior of a building, because it can handle plants with slow dynamics, time-variant disturbances and non-linear constraints [6]. MPC is comprised of two integral parts: an internal model to predict the future outputs and an optimizer to generate the optimal control signals. Due to the decreasing cost of applying data-driven methods to different complex plants, there has been a significant increase in utilizing intelligent and optimal control methods for Building Management Systems (BMS). Among the intelligent modeling methods, Artificial Neural Networks have gained a lot of attention since they can learn the thermal dynamics of a building pretty well and they are capable of efficiently predicting the future thermal behaviors of a building. They have been widely used for HVAC control [7-12] and energy consumption estimation applications [13–19]. HVAC systems have high non-linearity and delay which makes the control process sophisticated. An Artificial Neural Network (ANN) has been used as the internal model of the controller in order to predict the future outputs of the Air Handling Unit (AHU). Since ANNs have a non-linear nature, the problem becomes a Non-linear Model Predictive Control (NMPC) one. The most important task of NMPC is finding the optimal control inputs to apply to the actuators. Previous researches have demonstrated that Genetic Algorithm (GA) is the most effective tool for optimizing the performance of HVAC

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TmaxMaximum allowed temperature (°C)HVACHeating, ventilation and air conditioning systemsNARXNon-linear autoregressive network with exogenous inputsAHUAir handling unitANNArtificial neural networksCAVConstant air volumeGAGenetic algorithmVAVVariable air volumeBMSBuilding management systemMPCModel predictive controlPCBPrinted circuit boardNMPCNon-linear model predictive controlREARobust evolutionary algorithmPMVPredicted mean voteMREPMean of relative error percentagekTime stepHcControl horizonmi ret,zReturn air from zh zone (m³/s)pOutput delay numbersp <z< td="">Damper position of zh zone (%)qInput delay numberspFresh air damper position (%)r_zxth zone reference trajectoryr_aAmbient temperature (°C)\vec{X}Control leri input vectormi_cChilled water flow rate (kg/s)\vec{Y}Plant's outputSahuAHU status\vec{C}Control signalsCCourt,wCooling coil input water (kg/s)\vec{Y}_{train}Number of test patternsCCourt,wCooling coil output water (kg/s)\vec{Y}_{train}Number of training patternsT_zxth zone predicted temperature (°C)\vec{Y}_{train}Number of training patterns</z<>	Nomenclature		T _{min}	Minimum allowed temperature (°C)
AHUAir handling unitANNArtificial neural networksCAVConstant air volumeGAGenetic algorithmVAVVariable air volumeBMSBuilding management systemMPCModel predictive controlPCBPrinted circuit boardNMPCNon-linear model predictive controlREARobust evolutionary algorithmPMVPredicted mean voteMREPMean of relative error percentagekTime stepVariablesHcControl horizonm ret.zReturn air from zth zone (m³/s)zIndices for zonesIndices for zonesmdis.zDischarge air to the zth zone (m³/s)pPzDamper position of zth zone (%)qPraFresh air damper position (%)rzraAmbient temperature (°C) \vec{X} Control signalsCControl signalsCCCont,wCooling coil input water (kg/s)CCout,wCooling coil output water (kg/s)PtrainNumber of training patternsTzzth zone temperature (°C)Tzxth zone temperature (°C)TaNumber of test patternsCCout,wCooling coil output water (kg/s)PtestNumber of training patternsTzxth zone temperature (°C)TaStatemenare ret			T _{max}	Maximum allowed temperature (°C)
$\begin{array}{cccc} {\rm CAV} & {\rm Constant air volume} & {\rm GA} & {\rm Genetic algorithm} \\ {\rm VAV} & {\rm Variable air volume} & {\rm BMS} & {\rm Building management system} \\ {\rm MPC} & {\rm Model predictive control} & {\rm PCB} & {\rm Printed circuit board} \\ {\rm NMPC} & {\rm Non-linear model predictive control} & {\rm REA} & {\rm Robust evolutionary algorithm} \\ {\rm PMV} & {\rm Predicted mean vote} & {\rm MREP} & {\rm Mean of relative error percentage} \\ {\rm k} & {\rm Time step} \\ {\rm Variables} & {\rm H_c} & {\rm Control horizon} \\ {\rm H_p} & {\rm Prediction horizon} \\ {\rm H_p} & {$	HVAC	Heating, ventilation and air conditioning systems	NARX	Non-linear autoregressive network with exogenous inputs
VAVVariable air volumeBMSBuilding management systemMPCModel predictive controlPCBPrinted circuit boardNMPCNon-linear model predictive controlREARobust evolutionary algorithmPMVPredicted mean voteMREPMean of relative error percentagekTime stepVariables H_c Control horizonm ret,z Return air from zth zone (m ³ /s)zIndices for zonesIndices for zonesmdis,zDischarge air to the zth zone (m ³ /s)pOutput delay numbersP_zDamper position of zth zone (%)qInput delay numbersP_faFresh air damper position (%) r_z zth zone reference trajectoryT_aAmbient temperature (°C) \vec{X} Control signalsCG _{in,w} Cooling coil output water (kg/s) P_{test} Number of test patternsCCout,wCooling coil output water (kg/s) P_{train} Number of test patterns	AHU	Air handling unit	ANN	Artificial neural networks
MPCModel predictive controlPCBPrinted circuit boardNMPCNon-linear model predictive controlREARobust evolutionary algorithmPMVPredicted mean voteMREPMean of relative error percentage $Variables$ H_c Control horizon $\dot{m}_{ret,z}$ Return air from zth zone (m³/s)zIndices for zones $\dot{m}_{dis,z}$ Discharge air to the zth zone (m³/s)pOutput delay numbers P_z Damper position of zth zone (%)qInput delay numbers P_{fa} Fresh air damper position (%) r_z zth zone reference trajectory T_a Ambient temperature (°C) \vec{X} Controller input vector \dot{m}_c Chilled water flow rate (%) \vec{Y} Plant's output S_{ahu} AHU status \vec{C} Control signals $CC_{out,w}$ Cooling coil output water (kg/s) P_{train} Number of test patterns T_z zth zone temperature (°C) T_c Ctraining patterns	CAV	Constant air volume	GA	Genetic algorithm
NMPCNon-linear model predictive controlREARobust evolutionary algorithmPMVPredicted mean voteMREPMean of relative error percentage PMV Predicted mean voteMREPMean of relative error percentage $Variables$ H_c Control horizon $m_{ret,z}$ Return air from zth zone (m ³ /s) z Indices for zones $m_{dis,z}$ Discharge air to the zth zone (m ³ /s) p Output delay numbers P_z Damper position of zth zone (%) q Input delay numbers P_{fa} Fresh air damper position (%) r_z zth zone reference trajectory T_a Ambient temperature (°C) \vec{X} Controller input vector \dot{m}_c Chilled water flow rate (%) \vec{Y} Plant's output S_{ahu} AHU status \vec{C} Control signals $CC_{out,w}$ Cooling coil input water (kg/s) P_{test} Number of test patterns T_z xth zone temperature (°C) T_c $Cet a sciet temperature$	VAV	Variable air volume	BMS	Building management system
PMVPredicted mean voteMREPMean of relative error percentage $Variables$ H_c Control horizon $w_{ret,z}$ Return air from z th zone (m^3/s) H_p Prediction horizon $m_{dis,z}$ Discharge air to the z th zone (m^3/s) p Output delay numbers P_z Damper position of z th zone $(\%)$ q Input delay numbers P_a Fresh air damper position $(\%)$ r_z z th zone reference trajectory T_a Ambient temperature (°C) \vec{X} Controller input vector m_c Chilled water flow rate $(\%)$ \vec{Y} Plant's output S_{ahu} AHU status \vec{C} Control signals $CC_{out,w}$ Cooling coil input water (kg/s) P_{test} Number of test patterns T_z z th zone temperature (°C) P_{test} Number of training patterns T_z z th zone temperature (°C) P_{train} Number of training patterns	MPC	Model predictive control	PCB	Printed circuit board
VariableskTime stepVariables H_c Control horizon $\dot{m}_{ret,z}$ Return air from xth zone (m^3/s) p Prediction horizon $\dot{m}_{dis,z}$ Discharge air to the xth zone (m^3/s) p Output delay numbers P_z Damper position of xth zone ($\%$) q Input delay numbers P_fa Fresh air damper position ($\%$) r_z xth zone reference trajectory T_a Ambient temperature (°C) \vec{X} Controller input vector \dot{m}_c Chilled water flow rate ($\%$) \vec{Y} Plant's output S_{ahu} AHU status \vec{C} Control signals $CC_{in,w}$ Cooling coil input water (kg/s) P_{test} Number of test patterns T_z xth zone temperature (°C) P_{test} Number of training patterns T_z xth zone temperature (°C) P_{train} Number of training patterns	NMPC	Non-linear model predictive control	REA	Robust evolutionary algorithm
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H_p Prediction horizon $\dot{m}_{ret,z}$ Return air from zh zone (m^3/s) z Indices for zones $\dot{m}_{dis,z}$ Discharge air to the zh zone (m^3/s) p Output delay numbers P_z Damper position of zh zone $(\%)$ q Input delay numbers P_fa Fresh air damper position $(\%)$ r_z zh zone reference trajectory T_a Ambient temperature (°C) \vec{X} Controller input vector \dot{m}_c Chilled water flow rate $(\%)$ \vec{Y} Plant's output S_{ahu} AHU status \vec{C} Control signals $CC_{in,w}$ Cooling coil input water (kg/s) P_{test} Number of test patterns C_z zth zone temperature (°C) P_{train} Number of training patterns			k	Time step
$ \begin{array}{cccc} \dot{m}_{ret,z} & \mbox{Return air from $zth zone (m^3/s)} & z & \mbox{Indices for zones} \\ \dot{m}_{dis,z} & \mbox{Discharge air to the $zth zone (m^3/s)} & p & \mbox{Output delay numbers} \\ \dot{m}_{dis,z} & \mbox{Damper position of $zth zone (m^3/s)} & q & \mbox{Input delay numbers} \\ \dot{m}_{z} & \mbox{Damper position of $zth zone (m^3/s)} & q & \mbox{Input delay numbers} \\ \dot{m}_{z} & \mbox{Fresh air damper position (m^3/s)} & r_z & \mbox{zth zone reference trajectory} \\ \dot{m}_z & \mbox{Ambient temperature (°C)} & \vec{X} & \mbox{Controller input vector} \\ \dot{m}_c & \mbox{Chilled water flow rate (m^3/s)} & \vec{Y} & \mbox{Plant's output} \\ \dot{S}_{ahu} & \mbox{AHU status} & \vec{C} & \mbox{Control signals} \\ \dot{C}_{cout,w} & \mbox{Cooling coil input water (kg/s)} & \mbox{P}_{test} & \mbox{Number of training patterns} \\ \dot{T}_z & \mbox{zth zone temperature (°C)} & \mbox{Train means temperature} \\ \end{array}$	Variable	S	H _c	Control horizon
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P_z Damper position of zth zone (%)qInput delay numbers P_{fa} Fresh air damper position (%) r_z zth zone reference trajectory T_a Ambient temperature (°C) \vec{X} Controller input vector \dot{m}_c Chilled water flow rate (%) \vec{Y} Plant's output S_{ahu} AHU status \vec{C} Control signals $CC_{in,w}$ Cooling coil input water (kg/s) P_{test} Number of test patterns $CC_{out,w}$ Cooling coil output water (kg/s) P_{train} Number of training patterns T_z zth zone temperature (°C) T_c Cot signals	ṁ _{ret,z}	Return air from zth zone (m ³ /s)	Z	Indices for zones
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	P_{fa}	Fresh air damper position (%)	r _z	zth zone reference trajectory
	Ta	Ambient temperature (°C)	$\overrightarrow{\mathbf{x}}$	Controller input vector
S_{ahu} AHU status \overrightarrow{C} Control signals $CC_{in,w}$ Cooling coil input water (kg/s) $\overrightarrow{P}_{test}$ Number of test patterns $CC_{out,w}$ Cooling coil output water (kg/s) $\overrightarrow{P}_{train}$ Number of training patterns T_z zth zone temperature (°C)TStatistic construction	\dot{m}_c	Chilled water flow rate (%)	\overrightarrow{Y}	Plant's output
$CC_{in,w}$ Cooling coil input water (kg/s) P_{test} Number of test patterns $CC_{out,w}$ Cooling coil output water (kg/s) P_{train} Number of training patterns T_z zth zone temperature (°C)TSet a sint temperature	Sahu	AHU status		*
$\begin{array}{ccc} CC_{out,w} & Cooling coil output water (kg/s) & P_{train} \\ T_z & zth zone temperature (°C) & T_z & Set point temperature \end{array}$	CC _{in,w}	Cooling coil input water (kg/s)		6
I_z 2th zone temperature (C)	,	Cooling coil output water (kg/s)		
T_z zth zone predicted temperature (°C)	Tz			
	Τ̈́z	zth zone predicted temperature (°C)	± s	our point competitute

systems [20–24]. Therefore, GA has been used as the optimizer in this study.

Zhao et al. thoroughly investigated different methods for modeling building's thermal dynamics. It was shown that data-driven methods are most useful for on-line control applications in this literature. In addition, intelligent methods yield more accurate results than statistical methods which makes them more reasonable for control applications [25]. Afram and Janabi-Sharifi divided control strategies for HVAC systems into four categories. Then a rigorous comparison was made between these methods. Various experimental and simulation results of different control methods were brought up and investigated based on the established performance criteria in the literature. It was shown that MPC proves more useful in HVAC system control applications [4].

Huang simulated zone temperature and damper position in a Variable Air Volume (VAV) unit and controlled them using MPC. The MPC results showed better transient response compared to a PI controller [26]. Avci et al. developed an algorithm for determining the temperature set-point regarding variable electricity price in California and then tried to track the generated set-point by applying MPC [2]. Morosan et al. presented simulation of zone temperature regulation by using decentralized, distributed and centralized MPCs [27]. Privara et al. compared performance of MPC to a well-tuned controller with a weather compensator in a big university [28]. Oldewurtel et al. took into account the weather predictions and the uncertainty of the system. Then, results of a Stochastic Model Predictive Controller (SMPC), nonstochastic predictive controller or in other terms Certainty Equivalence (CE) Rule-Based Controller (RBC) and Performance Bound Controller (PB) were presented and compared with one another. The results showed that the best performance is obtained when the SMPC is applied [1]. Ferreira et al. designed and implemented MPC to maintain thermal comfort quantified as Predicted Mean Vote (PMV) index while minimizing energy consumption. They used ANN to model building's thermal behavior [29]. Liang et al. designed MPC for controlling a multi-zone VAV AHU and the simulation results were compared to the installed PID controller. It was shown that MPC outperforms the PID controller [6]. Siroky et al. computed set-point temperature for supply water and room temperature periodically and weather forecasts were downloaded and served as the MPC inputs. The results showed more than 15% energy saving potential for a large building's heating system [30]. Rehrl et al. compared both experimental and simulation results of two control methods: MPC and exact linearization. They concluded that in general MPC tracks the reference trajectory better than the other approach [31]. Fong et al. optimized the operation of a simulated HVAC system by means of a Robust Evolutionary Algorithm (REA) by determining the optimal set-point of chilled water supply temperature chiller and set-point of supply air temperature of AHU [32].

This paper addresses the problem of NMPC design and implementation for a multi-zone Constant Air Volume (CAV) air handling unit. The plant's outputs are the zones' temperature which are to track set-point temperature, while minimizing the energy consumption. The control signals in this work are damper positions related to each zone, chilled water's flow rate and the AHU status (on/off). NMPC problem could be divided into two main sections: internal model and the optimizer [33]. Artificial neural network serves as the controller's internal model, and its role is to predict the future temperature of each zone. The optimal value for each of the control signals is calculated by means of a genetic algorithm (which is the optimizer in this study) at each step and then these signals are applied to the AHU through actuators. The proposed NMPC strategy aims to minimize the electricity and gas energy carriers' consumption of the aforementioned AHU and the deviation from the set-point temperature of each zone.

The paper is organized as follows. In section 2 the AHU system along with the data logging system are described. Section 3, elaborates on the ANN model utilized for predicting the zones' temperature. In section 4, model predictive control method is succinctly described. In section 5, designing the proposed NMPC for the AHU is rigorously explained and then experimental results of applying the NMPC to the plant are presented and discussed in section 6. Section 7 concludes the paper.

2. AHU system

2.1. AHU system structure

Case study in this research is an AHU with 3 zones. It is categorized as a CAV air handling unit, which means that the volume of its input air is constant while the temperature of this air is variable. A simple schematic of the aforementioned AHU is shown in Fig. 1. First, the returned air from the zones enters the mixing chamber and there it is mixed with the fresh air (if the fresh air damper position is open). In the Download English Version:

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