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CO_2 Heat Pump for Simultaneous Cooling and Heating: Enhancing Efficiency through Model Predictive Control and Neural Network Identification

Jintao He[1], Yu Yao[1], Meiyan Zhang[1], Yonghao Zhang[1], Bowen Lu[1], Lingfeng Shi[1,*], Gequn Shu[1]

1 Department of Thermal Science and Energy Engineering, University of Science and Technology of China, Hefei 230027, China

(*Corresponding authors: slf@ustc.edu.cn)

ABSTRACT

The carbon dioxide heat pump for simultaneous heating and cooling is an exceptional technology; however, current research tends to excessively prioritize the overall system efficiency improvement, neglecting the alignment of the system with heating and cooling supply and demand. This oversight leads to the wastage of redundant heat or cold in practical applications, resulting in energy loss. Therefore, addressing this from a supply-demand perspective, this study proposes a model predictive control based on demand. It integrates a novel carbon dioxide heat pump structure to mitigate the loss of redundant energy. Furthermore, this approach utilizes neural network identification to reduce the online computational load of the model predictive control in the carbon dioxide heat pump system.

Keywords: carbon dioxide; simultaneous cooling and heating; model predictive control; neural network identification.

NONMENCLATURE

Abbreviations	
ANN	Artificial Neural Network
COP	Coefficient of Performance
HPS	Heat Pump for Simultaneous heating and cooling
MLP	Multilayer Perceptron
MPC	Model Predictive Controller
Symbols	
d	Disturbance
P	Power(kW)/Pressure(kPa)
Q	Heating and cooling capacity(kW)
T	Temperature(K)
u	Input
x	State
y	Output

1. INTRODUCTION

In the face of escalating global energy demand and mounting environmental concerns, energy conservation has garnered unanimous international support [1]. The refrigeration and heating processes in energy-intensive sectors account for 20% to 50% of total electricity consumption, emphasizing the need for simultaneous heating and cooling solutions [2-4]. A Heat Pump for Simultaneous heating and cooling (HPS) offer a viable answer, enabling the production of heating and cooling energy concurrently with reduced power input[5]. The utilization of HPS allows for the coupling of heating and cooling functionalities, enabling the simultaneous production of heating and cooling energy with a lower power input. For the working fluids of the HPS, synthetic refrigerants like hydrochlorofluorocarbons, hydrofluorocarbons and chlorofluorocarbons, infamous for their environmental impacts, are being phased out under international agreements such as the Montreal Protocol. As a natural alternative, CO_2, classified as A1, non-toxic, and non-flammable, has gained prominence. CO_2's eco-friendly attributes, along with its cost-effectiveness and superior thermal properties, make it an ideal choice for HPS applications. Additionally, CO_2 HPS systems excel in generating high-temperature hot water due to the temperature glide in the supercritical state, establishing them as a promising solution for simultaneous heating and cooling needs [6].

In the pursuit of maximizing the Coefficient Of Performance (COP) of CO_2 HPS system amid varying external environmental conditions and fluctuating demands for cold and heat sources, precise control of the internal parameters is paramount.

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The implementation of meticulous control strategies for cooling, heating loads, and environmental fluctuations is pivotal to significantly reducing power consumption during off-design conditions.

The Model Predictive Controller (MPC), with its flexible control framework, offers automatic optimization and robustness. Scholars like Wang [7] have successfully demonstrated the application of MPC to CO_2 heat pumps, underscoring its potential through dynamic system identification. Frison [8] conducted hardware-in-the-loop experiments, seamlessly integrating the controller into conventional heat pump systems. Thus, the direct application of MPC to CO_2 HPS systems is a viable approach.

The accuracy of model identification holds immense significance in model predictive control. Artificial Neural Network (ANN) stands out as an excellent method in this regard due to its strong nonlinear approximation ability. Afram et al.[9] developed a model predictive control based on Ann and introduced the BNMI algorithm for optimization, achieving a maximum savings of 73% under seasonal cost.

In the intricate landscape of CO_2 HPS system, MPC's flexibility becomes evident, offering a solution to the complex control challenges posed by CO_2 HPS system. By comprehensively considering various control variables, ANN-based MPC optimally addresses fluctuations in hot and cold demands as well as ambient temperature variations. This approach harmonizes with the intricate requirements of CO_2 HPS system, ensuring high efficiency throughout the entire operational cycle. Through meticulous control strategies, CO_2 HPS system can maintain its efficiency, effectively meeting the challenges presented by multi-variable control objectives.

The rest of this paper is as follows: the second part introduces the working principle and mathematical model of the CO_2 HPS system and the verification of the model; then the third part introduces the ANN-based MPC control method; finally, the fourth part compares the ANN-based MPC control method with the traditional PID control to prove the effectiveness of the former; finally, the fifth part is the conclusion.

2. MATERIAL AND METHODS

Due to the need of a certain amount of data for model identification through artificial neural network, in order to improve training efficiency and reduce costs, this study establishes a mathematical dynamic simulation model of simultaneous cooling and heating, which is used to study the feasibility of applying model predictive control based on artificial neural network to CO_2 heat pump with simultaneous cooling and heating.

2.1 *CO_2 HPS system description*

The CO_2 HPS system is depicted in **Fig.1**, consisting of three main parts: the red section serves as the heating part, providing heat; the blue section functions as the cooling part, supplying cold; and the purple section represents the environmental heat exchange part, balancing the heat and cold load. The basic principle is as follows: firstly, the cooled supercritical working fluid enters the regenerator and exchanges heat with the subcritical working fluid. Subsequently, the reheated supercritical working fluid undergoes a pressure drop after throttle, becoming subcritical working fluid. This subcritical fluid is divided into two streams. One stream absorbs heat from the environment in the environmental evaporator, raising its temperature. It then enters the regenerator and exchanges heat with the supercritical working fluid before being pressurized to supercritical state in the bypass compressor. The other stream absorbs heat in the refrigeration evaporator, producing cooling capacity. Finally, it enters the main compressor, where it is pressurized to supercritical state. The two streams are mixed after compression by the compressors and release heat through the condenser to provide heating capacity, initiating the next cycle. During operation, the system's heating and cooling loads are typically adjusted by regulating the water flow rates in the heating and cooling sections. Additionally, the system's temperature and pressure are controlled by adjusting the two compressors, thereby influencing the efficiency of the system's operation.

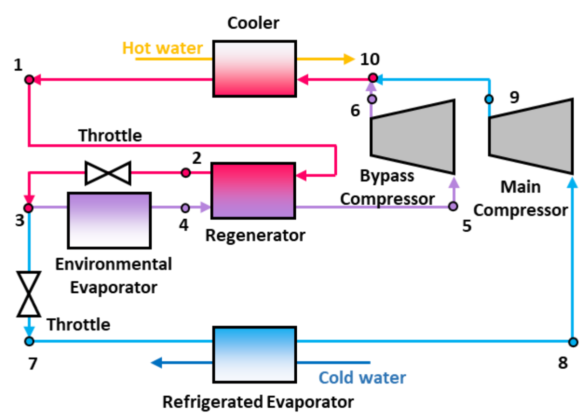


Fig. 1 Diagram of the system

2.2 *Dynamic simulation model description*

In order to implement the model predictive controller strategy based on artificial neural networks, a high-fidelity dynamic simulation model of the *CO_2 HPS system* is first established to generate data. This simulation model is constructed using the simscape fluids module in MATLAB/simscape software. Similar simulation models have been previously developed and validated in our previous work[10], and the details are not reiterated here.

2.3 Model predictive control based on artificial neural networks

Model Predictive Control based on neural networks is a control strategy that employs neural networks to establish the dynamic model of a system and uses this model for prediction at each control step. The fundamental idea behind MPC is to utilize the current system state and the model to predict the system's behavior over a future time horizon and then select control inputs that optimize the system's performance, as outlined in **Fig.2**. Artificial neural network play a crucial role in building the system model and providing the necessary information for prediction. In this study, a Multilayer Perceptron (MLP) model is utilized, which is a type of multilayer feedforward artificial neural network. MLP is a universal function approximation method capable of fitting complex functions, and its structure is depicted in **Fig.3**.

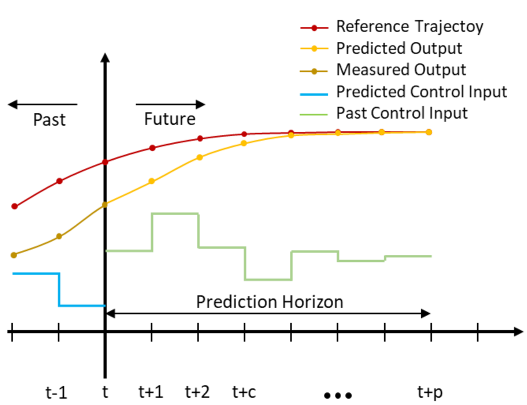


Fig.2 Schematic of model predictive control

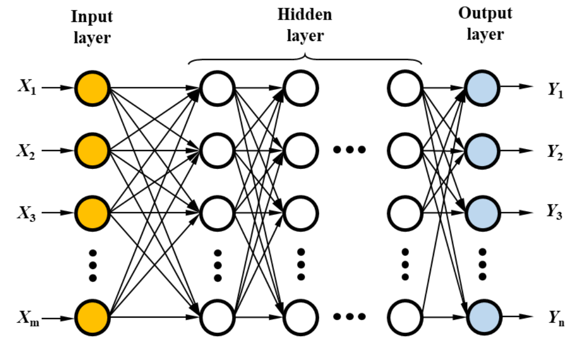


Fig.3 The topology of the multilayer perceptron

3. CALCULATION

3.1 System identification based on artificial neural networks

In this study, data generated from the established dynamic *simulation* model were utilized for the model identification of the CO_2 HPS system. Assuming that the CO_2 HPS system can be represented as a general discrete-time nonlinear state-space model:

$$x(k) = f(x(k-1), u(k-1), d(k-1)) \tag{1}$$

$$y(k) = h(x(k), u(k), d(k)) \tag{2}$$

In the equations (1) and (2), the vectors $\boldsymbol{x}$, $\boldsymbol{u}$, $\boldsymbol{d}$, and $\boldsymbol{y}$ represent the system's state, input, disturbance, and output, respectively. It is crucial to note that the precise form of the nonlinear system functions $\boldsymbol{f}(\cdot)$ and $\boldsymbol{h}(\cdot)$ is unknown. Therefore, learning from the data, we obtain the corresponding multilayer perceptron to represent the form of this nonlinear system function. The multilayer perceptron chosen in this study has 2 hidden layers and uses the hyperbolic tangent function as its activation function.

For the CO_2 HPS system, the essential states include the hot water outlet temperature T_{wh}, the cold water outlet temperature T_{wc}, the inlet temperature of bypass compressor T_b, the inlet temperature of main compressor T_m, the inlet pressure of cooler P_c, and the inlet pressure of refrigerated evaporator P_e. Manipulable inputs consist of the hot water mass flow rate M_{wh}, the cold water mass flow rate M_{wc}, the speed of bypass compressor ω_b, the speed of main compressor ω_{bm}, the opening of the throttle valve after the cooler x_{valve1}, and the opening of the throttle valve before the refrigerated evaporator x_{valve2}. The ambient temperature T_{amb}, being uncontrollable, is considered a disturbance. The system's outputs include the system's heating capacity Q_h, cooling capacities Q_c, and the power consumption of the compressors P_{comp}. Therefore, the specific parameters in the nonlinear state-space model are as follows: the states $x=[T_{wh},T_{wc},T_b,T_m,P_c,P_e]^T$, the inputs $u=[M_{wc}, M_{wh},\omega_b,\omega_m,x_{valve1},x_{valve2}]^T$, the disturbance $d=[T_{amb}]^T$, and the outputs $y=[Q_h, Q_c, P_{comp}]^T$.

Based on the above method, we established a control-oriented dynamic performance model of a carbon dioxide heat pump using artificial neural networks. The artificial neural network system identification model is validated using the established dynamic *simulation* model l, and the validation results are shown in **Fig.4**. The predicted states and outputs from the artificial neural network system identification model closely match the operating data from the physical model, with an average error of 0.4%. This indicates that the model successfully captures the dynamic characteristics of the CO_2 HPS system, making it suitable for use in MPC applications.

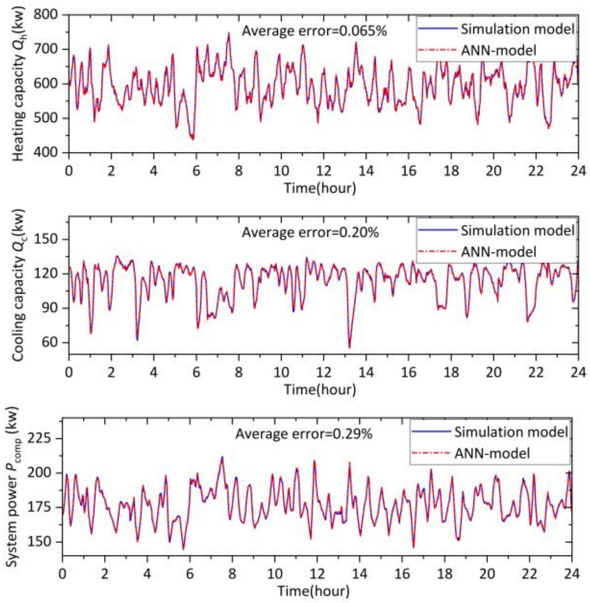


Fig.4 The validation of the ANN model

3.2 MPC methodology

The MPC method determines the inputs ***u*** for the next step by solving the objective function based on the control-oriented dynamic model, predicting the future operating states of the system. In this study, the primary objective of the MPC strategy is to minimize the total power consumption of the compressors for a carbon dioxide heat pump while ensuring the satisfaction of heating and cooling loads. Therefore, the objective function is formulated as follows:

$$\min_u J = \sum_{j=0}^{N_p} (a_j P_{comp}(k+j|k) + b_j |T_{wh}(k+j|k) - T_{wh,aim}| + c_j |T_{wc}(k+j|k) - T_{wc,aim}|)^2 \quad (3)$$

$$s.t.\ x_{min} \le x(k+j|k) \le x_{max} \quad \forall j \quad (4)$$

$$u_{min} \le u(k+j|k) \le u_{max} \quad \forall j \quad (5)$$

$$\Delta u_{min} \le \Delta u(k+j|k) \le \Delta u_{max} \quad \forall j \quad (6)$$

Where, N_p represents the prediction horizon, and $k+j|j$ denotes the state vector predicted at time $k+j$ given the information available at time k. P_{comp} represents the compressor power prediction, T_{wc} represents the cold water outlet temperature, and T_{wh} represents the hot water outlet temperature. a, b, and c are weighting factors penalizing different criteria. If the top priority is to strictly maintain the outlet water temperature at the required set value, then increase the weighting factors b and c. If minimizing the compressor power consumption is the priority and the outlet water temperature can be compromised, then increase the weighting factor a. For the constraint conditions, the state vector $x(k+j|k)$ is always limited within predefined minimum value x_{min} and maximum value x_{max} . The input vector $u(k+j|k)$ is also subjected to similar lower bound u_{min} and upper bound u_{max}. $\Delta u(k+j|k)$ signifies the difference between two consecutive inputs and is subject to similar lower bound Δu_{min} and upper bound Δu_{max} to prevent drastic changes in system components, ensuring safety.

In previous studies, researchers have commonly used a Proportional-Integral (PI) strategy to control input variables, maintaining the supply of cooling and heating, as well as the exit temperatures of cold and hot water, at target values. Therefore, this study adopts a similar PI control strategy as a comparative method for computation.

4. RESULT AND DISCUSSION

In this section, the MPC strategy is evaluated under given boundary conditions to demonstrate its effectiveness. To compare the performance of MPC, PI control is also implemented under the same boundary conditions. The simulation scenarios utilized real environmental temperatures from Hefei, China, for a period of 1 day (obtained from the China Meteorological Center), ranging from 13 to 27°C. The demand curve for cooling and heating in the combined cooling and heating supply system is derived from a typical daily load profile of a food processing factory in Hefei, China, obtained after our investigation. Specific boundary conditions for the case study are shown in **Fig.5**.

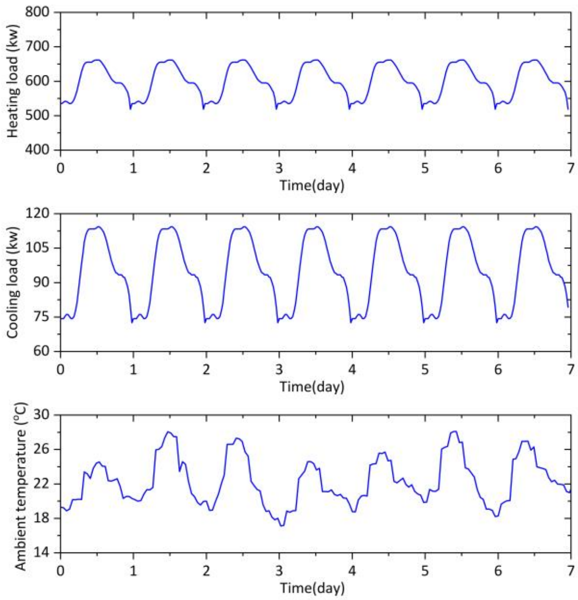
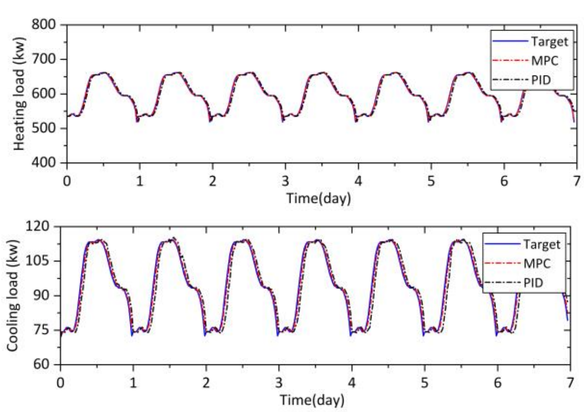


Fig.5 The boundary conditions for the test case

The sampling time of both PI control strategy and MPC control strategy is designed to be 3mins, while the prediction time of MPC is set to 15mins. In this setting, comparison of the two strategies under the given boundary conditions is shown in **Fig.6**, indicating the results of the heating and cooling loads. From the results, it can be observed that both PID and MPC can track the heating and cooling loads. However, due to its nature as a feedback control system, PID exhibits a noticeable delay in tracking the load. The average relative error under the PID control strategy is 1.062%. On the other hand, MPC, considering the current control's impact on the future, exhibits a smaller delay in control compared to PID. The average relative error under the MPC strategy is 0.146%. This suggests that MPC has a stronger ability to track the load.



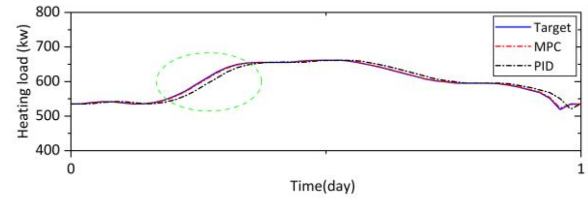


Fig.6 Comparison of the cooling and heating capacities of the system under different strategies

Fig.7 illustrates the power consumption of compressors under different strategies. From the figure, it can be observed that the power consumption under MPC control is lower than that under PID control, with an average power reduction of 1.45%. PID control indirectly reduces compressor power by tracking the optimal exhaust pressure to adjust the COP. In contrast, MPC directly calculates the total compressor power over a certain period to minimize it. Therefore, the control effect of MPC will be better.

It can be seen that when the ambient temperature rises, the difference in compressor power between MPC and PID control is not significant. This is because PID control lags in cooling and heating supply, causing MPC control to require higher cooling and heating supply outputs, as shown in **Fig.6**. Therefore, although the COP under MPC control is slightly higher, the need for higher cooling and heating supply output in MPC control makes the difference in compressor power between MPC and PID control not significant when the ambient temperature rises.

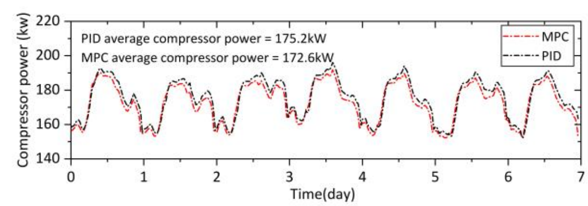


Fig.7 Comparison of the compressor power of the system under different strategies

In summary, MPC predicts the system behavior for a future period using the trained ANN model. This ability allows MPC to respond to potential changes in the future, thereby enhancing the system's stability and performance. However, based on the current results, the improvement from MPC seems relatively small. This could be due to our assumption that the isentropic efficiency of the compressor remains constant during operation, which might not hold in real-world scenarios, especially under non-design conditions. This oversight could worsen the performance of the PID control strategy, while MPC, considering the overall efficiency of the compressor, remains relatively stable. Additionally, the case study did not account for the return water temperatures in both the cooling and heating sides, which are common disturbances affecting the effectiveness of the heat pump.

In conclusion, there are still limitations in the current work. However, the control method based on ANN-MPC, due to its predictive nature and multivariable control, is suitable for the operation control of CO2 heat pumps, which often involve multiple objectives in cooling and heating.

5. CONCLUSIONS

This paper addresses the optimization of the CO_2 HPS system operations by proposing a ANN-based MPC strategy, aiming to improve the overall system performance by adjusting the outlet water temperature. Traditional feedback control strategies (proportional-integral control strategy) maintain a fixed supply water temperature in the CO_2 HPS system operations. However, under complex and time-varying conditions, these strategies fail to achieve system performance optimization. Unlike the traditional feedback control strategies, the MPC strategy, based directly on the artificial neural network control model, provides optimal operating inputs through the objective function, effectively minimizing compressor power consumption and achieving efficiency optimization. The specific conclusions are as follows: First, a control-oriented artificial neural network model is established using data, with an average error of 0.4%. This indicates that the data-driven model successfully captures the dynamic performance of the CO_2 HPS system. Secondly, the proposed ANN-MPC strategy is evaluated in a case study from the food industry. Compared to the traditional PI control strategy, the ANN-MPC strategy reduced compressor power consumption by 1.45% while ensuring the cooling and heating capacity. This demonstrates that ANN-MPC is an effective and feasible control strategy for improving the overall performance of the CO_2 HPS system operations.

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