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Proceedings of the 7th International Seminar on ORC Power Systems

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Advanced control of compressor inlet temperature in supercritical CO_2 Brayton cycle

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ABSTRACT

The supercritical CO_2 (sCO_2) Brayton cycle has gained much interest because of its flexibility, compactness and high efficiency. The sCO_2 at the inlet of compressor should work near the critical point to obtain high system efficiency, while the physical properties of sCO_2 near the critical point change dramatically, which brings great challenges to the control of the compressor inlet temperature. At present, cooling far from the critical point and adjusting the cooling water flow rate with Proportion-Integration-Differentiation (PID) controller is the commonly used method, but it loses system efficiency and may be out of control sometimes. Therefore, in this study Linear Model Predictive Control (LMPC) and Deep reinforcement learning (DRL) are used to control the compressor inlet temperature and compared with PID. A dynamic model of a recompression sCO_2 Brayton cycle is established, and the cooler model is carefully validated against experiment data. The results indicate that both the LMPC and DRL can control the sCO_2 temperature near the critical temperature much better than the PID. LMPC works the best because the cold end parameters fluctuate slightly and the cooler model can be regarded as approximately linear, thus LMPC can find almost the global optimal solution. Nevertheless, DRL control exhibits the fastest real-time computation ability and proves good extrapolation ability. 596

1 INTRODUCTION

The supercritical carbon dioxide (sCO_2) Brayton cycle has gained more and more interesting due to its advantages of high thermal efficiency, compactness of components, wide temperature range application (Açıkkalp *et al*.,2017) and so on. It has been regarded as the potential power conversion equipment for next generation in numerous applications, including nuclear, solar, fossil fuel and waste heat recovery (Gao *et al*.,2021; Liang *et al*.,2020; Battista *et al*., 2019). These advantages benefit greatly from the high density and low compressibility of CO_2 near its critical point (304.1 K, 7.38 MPa) at the inlet of compressor (Dostal *et al*.,2004).
However, the physical properties of sCO_2 near the critical point change dramatically, which brings significant challenges to the control of the compressor inlet temperature of sCO_2 (Hacks *et al*., 2019). The closer this temperature is to the critical temperature, the smaller the compressor power consumption and the higher the system efficiency, but it is more difficult to control at a stable value, and sometimes it is easy to fall into a trans-critical state, resulting in compressor damage. Therefore, the compressor inlet temperature of sCO_2 in many studies are far from the critical point to ensure the safety operation with the expense of reducing thermal efficiency. Zhang *et al*. (2022) established the dynamic model of Brayton cycle with the compressor inlet temperature of sCO_2 of 35 °C and the cycle efficiency is 20.616%. Clementoni *et al*. (2017) also analyzed the transient power operation of a sCO_2 Brayton cycle with the compressor inlet temperature of sCO_2 of 35.5°C, the cycle efficiency under 35% load is 7.4%. Zhou et al. (2021) found that when the compressor inlet temperature of sCO_2 increase from 306 K to 312 K, the system efficiency decreased by two percentage points.
The compressor inlet temperature of sCO_2 is usually controlled at the set value in most studies to ensure the safe operation of the system. At present, this temperature is usually controlled by the cooling water mass flow rate with a Proportion-Integration-Differentiation (PID) controller. For example, Olumayegun and Wang (2019) used the PID controller to keep the compressor inlet temperature of

sCO_2 at the set value. Moisseytsev *et al*. (2011) included a cooler bypass PID control to maintain the compressor inlet temperature, the results demonstrate that the single cooler bypass valve is out of operation when the temperature is expected to decrease much, and it has to cooperate with cold source mass flow rate control. Besides, the PID may fail sometimes.
From the above review, it can be found that the current commonly used control method for compressor inlet temperature of sCO_2, that is, far from the critical point combined with PID controller, not only loses the system efficiency, but also may be out of control in some conditions. Therefore, it is necessary to study more advanced control method to control the temperature more stably near the critical temperature, so as to improve system safety and efficiency.
To this end, the linear model predictive control (LMPC) and deep reinforcement learning (DRL) control are proposed to control the compressor inlet temperature of sCO_2, which have not been applied in sCO_2 Brayton cycle, while exhibited good performance in other control problem such as energy management and unmanned vehicles. For this purpose, the dynamic model of a recompression sCO_2 Brayton cycle with the compressor inlet temperature of sCO_2 near the critical point is established in Simulink/Matlab to ensure the high system efficiency, and the component model of cooler is carefully validated against experiment data. Based on these, the performance of the two control methods is compared with the traditional PID controller.

2 MODELLING DESCRIPTION

Extensive research has been conducted on system configurations and layouts of the sCO_2 Brayton cycle such as reheating, recuperation, intercooling, and recompression. The recompression Brayton cycle stands out owing to its simple layout simplicity and high cycle efficiency. Many sCO_2 experiment system are the recompression cycle, such as Sandia's system. The object of this study is also a recompression sCO_2 Brayton cycle (RCBC) system, the configuration is showed in Figure 1. The main components include a heater, high-temperature recuperator (HTR), low-temperature recuperator (LTR), cooler, main compressor (MC), recompressor (RC), high-pressure turbine (HT), low-pressure turbine (LT), pipes, and valves. The HT is coaxial with MC and is called turbine-and-compressor1 (TAC1); similarly, the LT coaxial with RC is named TAC2. The system design parameters are showed in Figure 1 and Table 1. It should be noticed that the design parameters are not only optimized with system thermodynamic models, but also limited by the actual equipment manufacturing capacity, because the system experiment bench is being built according to the design parameters. For example, although the higher the turbine inlet temperature brings the higher cycle efficiency, but it is hard for manufacturing the boiler and turbine, so the turbine inlet temperature is designed at 550 °C. 597

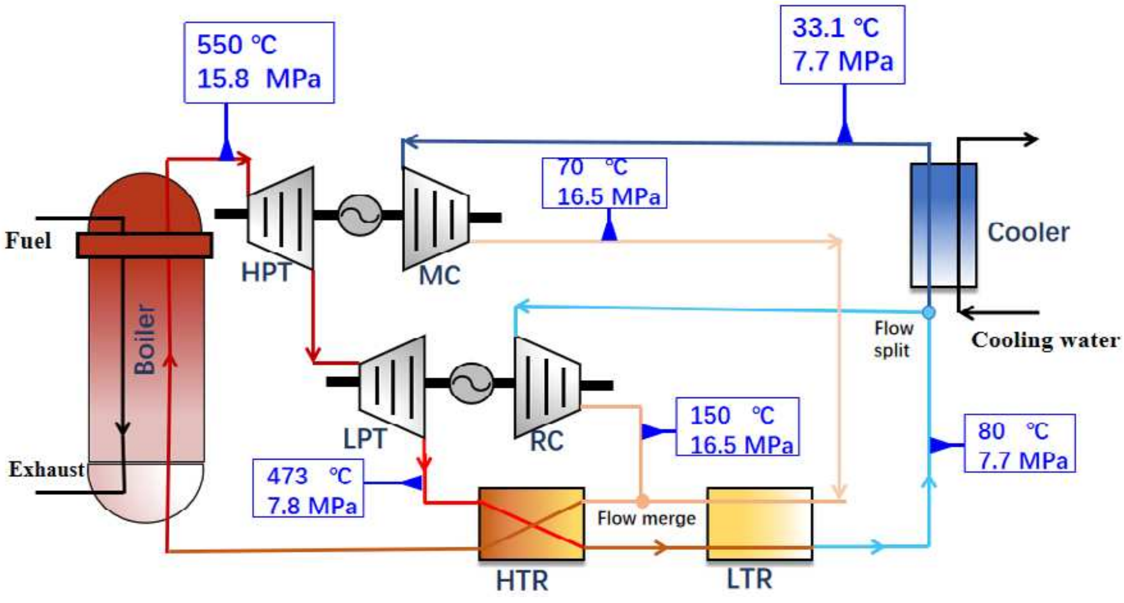


Figure 1: Schematic layout of the system

Table 1: Design parameters of the RCBC dynamic model

Process variable	Unit	Value
Net Power	kW	455.5
Cycle Efficiency	%	34.2
Cycle Flow of sCO_2	kg/s	9.76
Split ratio	/	0.38
MC/RC Isentropic Efficiency	%	68/68
HT/LT Isentropic Efficiency	%	83/77
HTR/LTR Regenerative Rate	%	95/89
Rotation Speed of MC	rpm	71670
Rotation Speed of RC	rpm	109055
Cooling Water Flow	kg/s	13.97
Cooling Water Temperature	℃	25

2.1 Dynamic modelling

The dynamic model of the system is developed by connecting the component models according to the thermodynamic relationship. The modelling process is briefly described in Figure 2 and below content, and more detailed description is available in our previous work (Wang *et al*., 2022).

The dynamic model of the RCBC system is established in the MATLAB/Simulink environment based on the boundary condition provided in Figure1 and Table 1. The properties of CO_2 are obtained by Refprop 9.0. All heat exchangers including a reheater, a HTR, a LTR and a cooler are modeled using Finite Volume method, because no phase change exists in supercritical station. The heat exchanger is discretized into N control units, and each control unit is modeled based on the mass and energy conservations. The heat transfer coefficient of heat source in the boiler is gained from Horst *et al*. (2013), which has been provided suitable for high temperature gas outside the tube heat exchangers. The Ptukhov-Krasnoshchekov-Protopopov correlation from Pitla *et al*. (1998) is applied to CO_2 which are in supercritical phase and has no phase change. The coolant working fluid in the cooler is non-phase change cooling water, so the Petukhov-Kirillov correlation from Gelbe *et al*. (2010) is adopted. These heat transfer coefficients are listed in Table 2.

The zero-dimensional static model is adopted for turbomachinery for its faster response speed compared with heat exchangers. The performance maps from Sandia (Wright *et al*., 2010) are used for accurately predicting the performance of the compressor under off-design conditions. Two dimensionless parameters, including flow and ideal head coefficients, are introduced to describe the performance of the compressors, and the turbine is simplified as an unchoked nozzle model (Bian *et al*., 2022).

Additional pipes and valves are installed among adjacent components. The linear valve model is adopted in this study, the pipe is modeled based on the conservation of mass and energy, as well as the pressure drop equation.

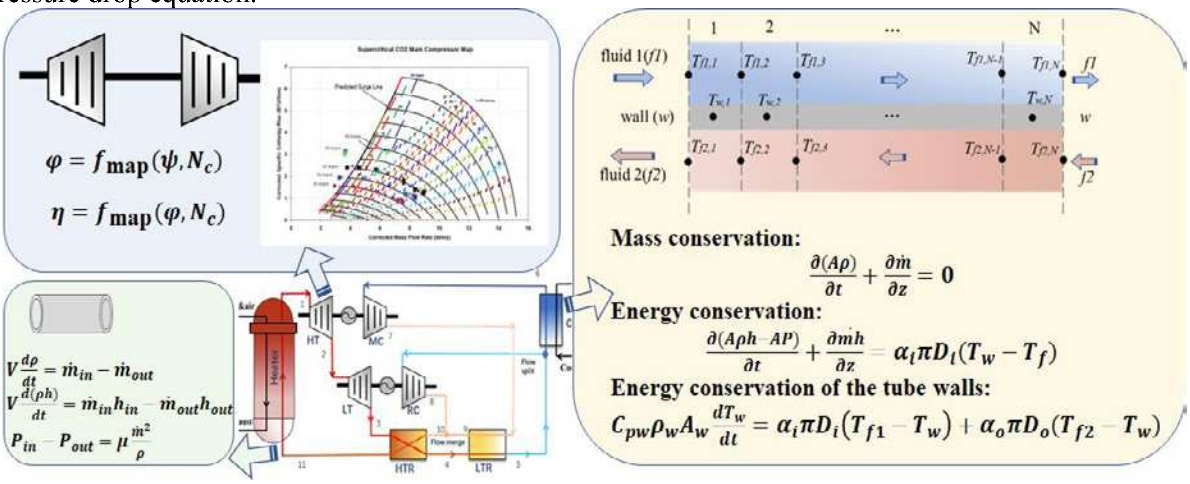


Figure 2: System modelling process

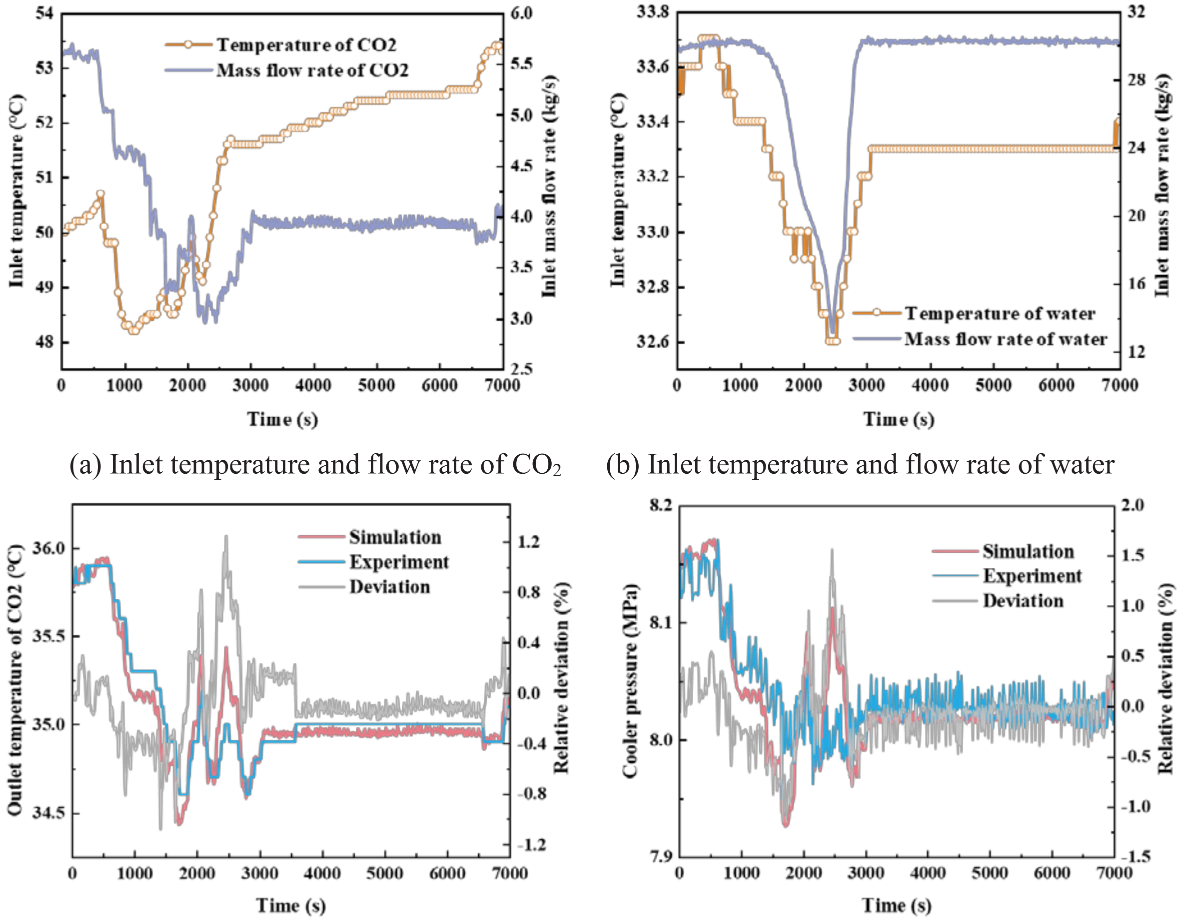
Table 2 Heat transfer correlations

Parts	fluids	Heat Transfer Correlations
Boiler/HTR/LTR/Cooler	sCO_2	$Nu = \frac{(f/8)\cdot Re\cdot Pr}{12.7(f/8)^{0.5}(Pr^{2/3}-1)+1.07}(\frac{\overline{C_p}}{C_{pb}})^{0.35}(\frac{k_b}{k_w})^{-0.33}(\frac{\mu_b}{\mu_w})^{0.11}$
Boiler	Heat source	$\alpha_o = 1.72\frac{\lambda}{d_o^{0.4}}(\frac{d_e w_n \rho}{\mu})^{0.6}(\frac{C_p\mu}{\lambda})^{\frac{1}{3}}(\frac{\mu}{\mu_w})^{0.14}$
Cooler	Water	$Nu = \frac{(f/8)RePr}{12.7(f/8)^{0.5}(Pr^{2/3}-1)+1.07}$

2.2 Model validation

As mentioned in the start of Section 2, the system experiment bench is being built according to the design parameters in Figure 1 and Table 1. The entire system has not been finished, but the compressor test bench with a cooler has been completed. Therefore, the dynamic model of the cooler which is focused in this study can be validated against the corresponding component experimental data.

By changing the experimental boundary conditions, including inlet temperature and flow rate on both the hot and cold sides, these parameters are taken as input parameters of the cooler model. The outlet temperatures on both of the hot and cold sides, and the cooler pressure are taken as output parameters. The input parameters are shown in Figures. 3(a) and (b). The validation results shown in Figures. 3(c) and (d) are the outlet temperature and pressure of CO_2, which demonstrates that the accuracy of the model is sufficient for further simulation.



(a) Inlet temperature and flow rate of CO_2 (b) Inlet temperature and flow rate of water

(c) Outlet temperature of CO_2 (d) CO_2 pressure

Figure 3: Model validation results of the cooler

3 CONTROL DEVELOPMENT

The compressor inlet temperature of sCO_2 is usually controlled by the mass flow rate of cooling water which can be adjusted by the water valve or the water pump speed. In this section, three control methods of LMPC, DRL, and PID are used to control the temperature all by adjusting the cooling water mass flow rate. The description of each control method is as follows.

3.1 PID control

At present, the PID control is the most widely used, owing to its simplicity and technical maturity. The schematic of PID control is shown in Figure 4. The sCO_2 temperature at the outlet of cooler (the compressor inlet temperature of sCO_2) is compared to the reference temperature and generate the tracking error inputted to the PID controller, in which the action signal is calculated and sent to the actuator such as cooling water valve. The PID parameters are tuned by linearizing the cooler model at the design condition, and they are -0.498 (P), -0.083 (I) and 15.706 (D), respectively.

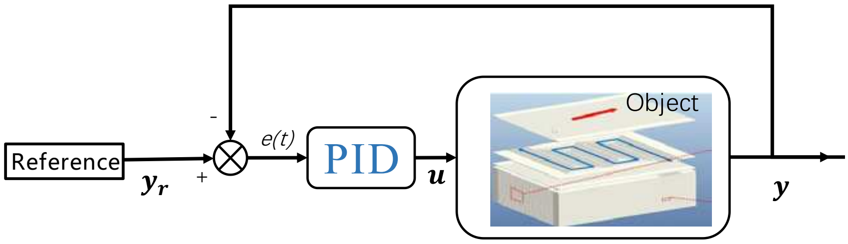


Figure 4: Schematic of PID control method

3.2 LMPC control

As mentioned in the introduction, the PID controller works well under small and slow transient operations, while it may have difficulties in fast and violent transient conditions, owing to the nonlinearity of the cooling process, and the PID is not an optimized control method.

Model predictive control (MPC) is a kind of optimized control method and has been proved to be effective in parameter tracking control in other applications, such as tracking the temperature of a biochemical reactor for yeast fermentation (Lawrynczuk *et al.*, 2008a). Therefore, in this work MPC is applied to control the compressor inlet temperature of sCO_2. To achieve real-time optimized control during system operation, the prediction models used in MPC methods must not be overly complex. Owing to the nonlinearity and complexity of the cooler model, in this work a linearized cooler model under the design condition is used for MPC optimization with a quadratic program solver. The model mismatch generated by the linearization was corrected using feedback. The schematic of the LMPC control method is showed in Figure 5. 600

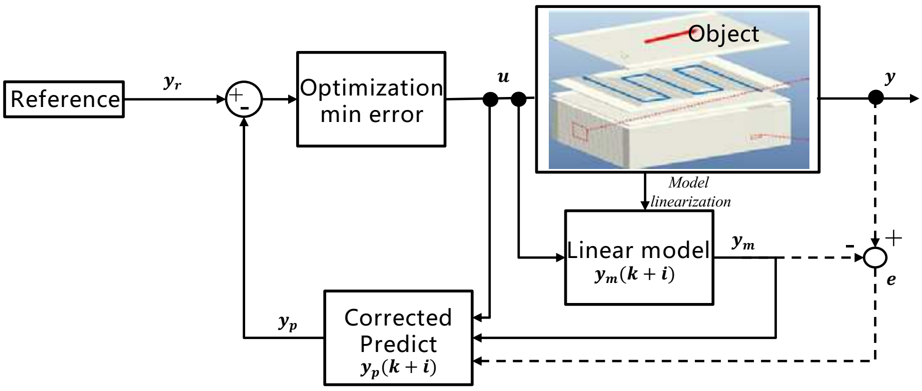


Figure 5: Schematic of LMPC control method

3.3 DRL control

Reinforcement learning (RL) algorithms mimic the learning mechanism of human brain. An RL agent observes and interacts with the environment to learn how to take optimal actions. DRL is the combination of deep learning and RL, possessing the strong nonlinear mapping capability of the former and the decision-making ability of the latter. Therefore, DRL can solve complex control problems and it has been proved to be effective for the temperature control in Organic Rankine Cycle (Wang *et al*., 2022b).

Compared to the LMPC, DRL can make the optimization offline with complex mechanism model which can reflect the nonlinear process more accurately through repeated training and guarantee real-time decision making. The key elements in the DRL are the agent (a deep neural network), environment (the cooler model), observation (key state parameters), action (cooling water valve opening), and reward. During the training process, the agent learns how to take actions under each observed state to obtain the maximum reward by constantly interacting with the environment.

A DRL control of the compressor inlet temperature of sCO_2 is proposed in this work as illustrated in Figure 6. Therein, the agent is the controller of a deep neural network; the environment is the cooler model; the observation variables are the arithmetic average temperature and pressure of the sCO_2 in the cooler, their change rates, and the tracking and accumulative errors, six variables in total; the action is the cooling water valve opening; the reward means the control performance, that is the less temperature tracking error, the larger reward, and the reward function is shown as Equation (1). The training method used in this work is deep deterministic policy gradient (Lillicrap *et al*., 2016a).

$$r = 8(|e|< 0.05) + 5(|e|< 0.1 \,\&\&\, |e|\geq 0.05) + 3(|e|< 0.3 \,\&\&\, |e|\geq 0.1) + (|e|< 0.5 \,\&\&\, |e|\geq 0.3)$$
$$-(|e|\geq 0.5) - 5(\frac{da_t}{dt} \bullet \frac{da_{t+1}}{dt} < 0) - 100(T < \min T \,||\, T > \max T) \quad (1)$$

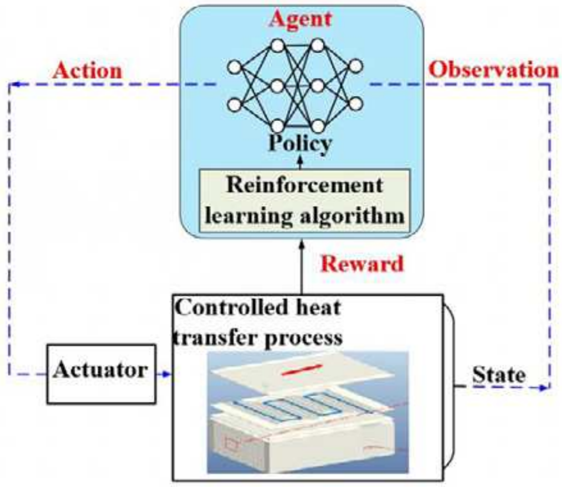
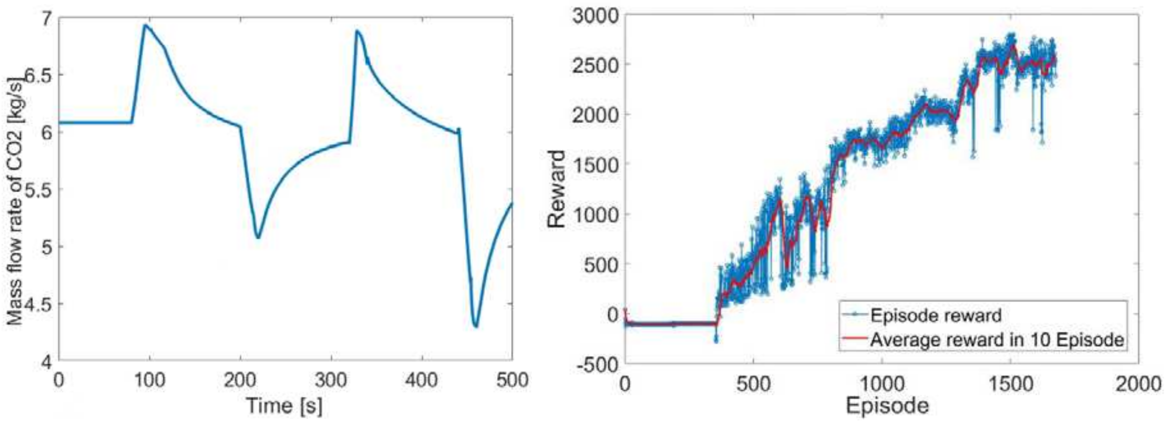


Figure 6: Schematic of DRL control method

During the training process, only the mass flow rate of the sCO_2 changes as shown in Figure 7(a), and other boundary conditions of the cooler are constant. After 1700 episodes of training, the result is converged as shown in Figure 7 (b).



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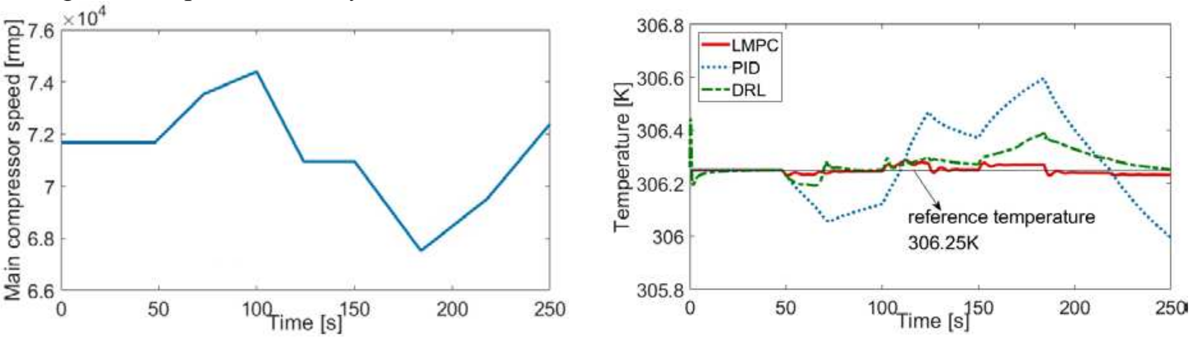
(a) Varying boundary condition during training (b) Training process

Figure 7: Training of the DRL controller

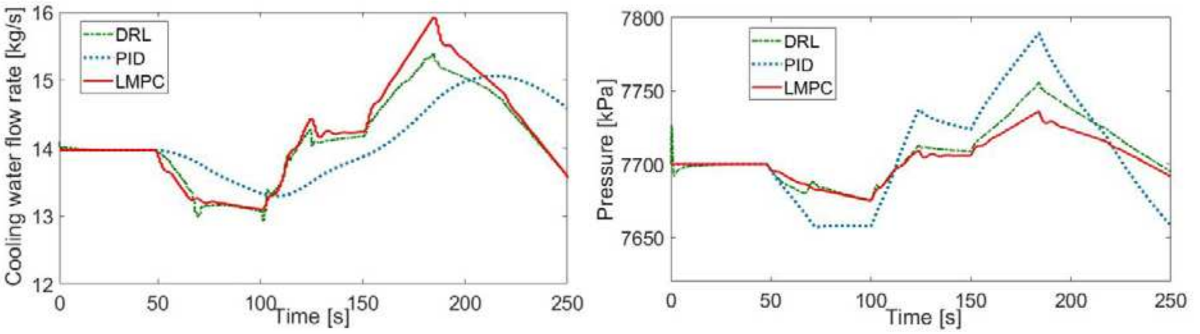
4 RESULT AND DISCUSSION

When the main compressor speed changes as shown in Figure 8(a), the LMPC, PID and DRL controllers for the compressor inlet temperature of sCO_2 are simulated in the entire system model to evaluate the control performance as shown in Figure 8(b). It should be noted that the varying mass flow rate of the sCO_2 in the cooler in this section is not the same as that in the DRL control training process, aiming at testing the extrapolation ability of the DRL control.



(a) Transient signal of the main compressor speed (b) Temperature control results

Figure 8: Temperature control results for various controller under transient main compressor speed



(a) Variation in the pressure in cooler (b) Variation in the mass flow of cooling water

Figure 9: Temperature control results for various controller under transient sCO_2 mass flow rate

It can be found that the compressor inlet temperature of sCO_2 can be controlled within ± 0.35K around the reference temperature under PID control, while that is ± 0.05K under LMPC control and almost ± 0.15K under DRL control. PID does not belong to optimal control, so its control effect is naturally inferior to the other two optimal control methods. LMPC can control the temperature fluctuation of sCO_2 in a very small range. In this range, the model of the cooler can be considered as a linear model, and the global optimal control trajectory can be found for the linear model. Therefore, it can be said that the control trajectory of LMPC is almost the global optimal. However, the convergence result of DRL optimization algorithm may be a local optimum, and it is not easy to judge whether the convergence result is a global optimum. Therefore, DRL does not have obvious advantages over LMPC when the model can be approximately linear in such a small range of state fluctuations.

As can be seen from the Figure 9, more accurate and stable temperature control leads to smaller fluctuation of the pressure in the cooler, which is conducive to maintaining the safe operation of the main compressor. However, the fluctuation of the cooling water mass flow rate of MPC is the largest to get the most accurate temperature control.

Nevertheless, DRL control still exhibits the fastest real-time computation ability during the simulation process, because its optimization calculation is carried out offline, and online it only needs to take the best action according to the trained rules. By contrast, the LMPC needs to be optimized online. For the controller, real-time is a very important performance index. On the other hand, as shown in the simulation results, DRL control proves good extrapolation ability. If the training sample can be enlarged and the training parameters can be optimized, DRL may obtain better control effect.

5 CONCLUSIONS

A dynamic model of the recompression sCO_2 Brayton cycle system is designed near the critical point to obtain high thermal efficiency, and the cooler model is carefully validated. LMPC and DRL control are used to control the compressor inlet temperature of sCO_2 and compared with traditional PID. The conclusions are as follows:

The performance of PID controller with constant parameters is not satisfactory under transient dynamic conditions. The LMPC controller is able to remain the smallest tracking error, because the cooler model is almost linear in such a small range of state fluctuations, and the LMPC can almost find the global optimal solution. By contrast, DRL controller is easy to fall into a local optimal solution, so the control effect is inferior to the LMPC, but much better than the PID. Nevertheless, DRL control still exhibits the fastest real-time computation ability during the simulation process, because its optimization calculation is carried out offline, which is a very important performance index for the controller. Besides, DRL control proves good extrapolation ability. It is believed that the DRL may have more advanced than MPC for more complex nonlinear problem and under the conditions with large uncertain disturbance.

NOMENCLATURE

RCBC	Recompression supercritical CO_2 Brayton Cycle
HTR	High-temperature recuperator
LTR	Low-temperature recuperator
HPT	High-pressure turbine
LPT	Low-pressure turbine
MC	Main compressor
RC	Recompressor
LMPC	Linear Model predictive control
MPC	Model predictive control
DRL	Deep reinforcement learning

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The ORC conference, organized biennially, stems as the only conference that is specific to ORC technology, therefore gathering a diverse community whose affiliation spans across all the interested stakeholders, not only in this particular technology but also and in a broader context, in the energy transition. Original equipment manufacturers, professional associations, end-users, investors, policy makers, academics, scientists feel at home at ORC 2023.

The almost 100 proceedings in this book cover a wide variety of topics, from fundamentals to system integration through component design, accounting for thermodynamic performance as well as component design. In addition to this, and as a new track in 2023, works on heat pump technology were also accepted in order to raise awareness of the strong ties between both technologies, specifically in energy storage applications.

This book provides an excellent overview of the current maturity of power systems based on Organic Rankine Cycle technology for applications as diverse as geothermal and waste heat recovery in industry or downstream of other prime movers (e.g., marine applications). It is also an excellent source of information to understand the current challenges faced by the technology, stemming from a very competitive market and increasingly stringent environmental regulations.

The organizers of ORC 2023 hope that the reader finds this work as exciting as the attendees to the conference and, maybe, make the decision to join the 8th edition to the conference in 2025.

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