INTERNATIONAL JOURNAL OF APPLIED RESEARCH AND TECHNOLOGY
ISSN 2519-5115
IJART- Vol-9, Issue-2, April, 2024
Available Online at http://www.ijart.info/
DOI: https://doi.org./10.24163/ijart/2017/9(2):51-69

ARTIFICIAL INTELLIGENCE ALGORITHM USED TO GET AN IMPROVED CONTROL IN INDUSTRIAL PROCESS OF METAL CASTING

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ABSTRACT

Keeping the level of steel in the mold of the continuous casting process constant is fundamental for the quality of the steel produced and, consequently, its commercial value. It is challenging, considering the several disturbances that cause undesired variations in the mold level. The aim of this paper is to apply a reinforcement-learning algorithm in order to control process of metal casting. Under different billet specifications and interference conditions, an accuracy of 80% of liquid level in the mold and a stopper rod opening degree stability rate of 75% can be achieved, which is 4.29% and 3.17% higher than those for the baseline algorithms, respectively.

Received: February 22, 2024
Revised: March 25, 2024
Published: March 31, 2024

Keywords- mold level; continuous casting; bulging disturbances, Soft Actor–Critic controller

INTRODUCTION

In recent years, the steel continuous casting has been optimized through careful integration of electro-mechanical sensors, computer-control, and production planning to provide a highly automated system. A complex control task as the mould level control (MLC) is very important for avoiding several products defects and keep down casting interruptions [1]. These reasons are the motivations of several types of research on this topic [2], [3]

Continuous casting processes of slabs or round billets is a real time industrial process in which the casting products are continuously produced from molten steel. The molten steel is poured into a mould through a ladle and a tundish, and the steel surface layer is solidified. The slab is extracted from the mould by a pinch roll, completely solidified by cooling water, cut to a specified length by a cutter and forwarded to the following process.

The term “controlled pouring” includes a large number of process-oriented control tasks and adaptation controller tasks, supervisory SCADA/MMI [4], which for example, allow casting to be started automatically and enhance the reliability of casting process [5]. The mould steel level control is only a small part of the control system but it is very important. Especially, the mould bath level control has a great effect on the surface quality of cast slab and billets and

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yield, so that the fluctuation of steel level position has to be closely controlled, as it is an important factor in process control [6]. Fig. 1 shows the technological scheme of mould steel level control.
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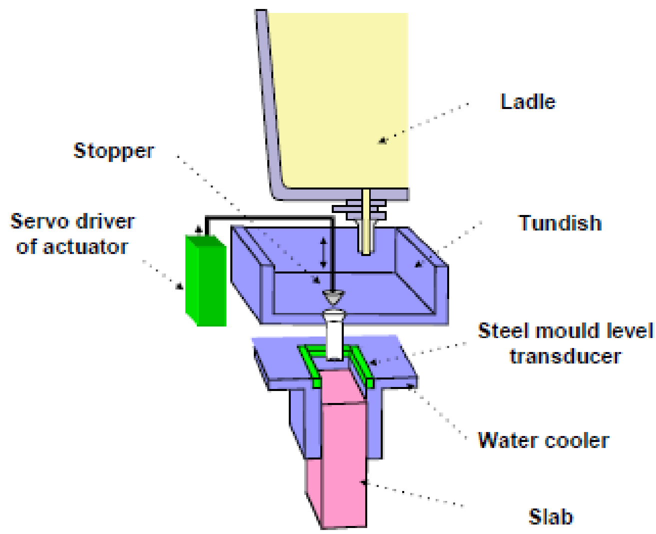

Fig. 1. Technological scheme of mould steel level control

PROBLEM MODELING

One of the main tasks of the control system is to keep the level of molten metal in the mould constant. In principle, two procedures are employed, varying the flow of liquid metal from the tundish to the mould or varying the speed at which the strand is withdrawn (see Fig. 2). In case of high quality requirements, the input flow control is preferred. A mould steel level control system consists of several parts.

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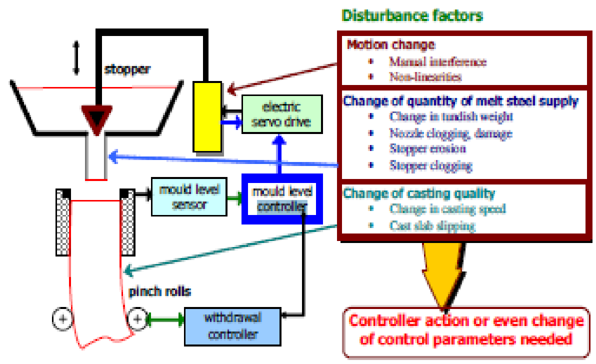

Fig. 2. Mould level control system and the disturbance factors

Automatic casting technology means that the stopper rod automatically completes the filling of liquid steel in the mold in the initial stage of continuous casting, making the process of raising the liquid level in the mold fully controllable and reaching the start level of the pulling machine within the specified time window. The setting of the target liquid level curve was in accordance with reference [7], but in order to better understand the process of raising the liquid level in the mold, the specific liquid level value is abstracted in this paper, and the final curve is shown in Fig. 3. The period from 0 to t_5 is the automatic casting process. The liquid level in the mold reaches the start level h_2 of the pulling machine at t_5 and then switches to closed-loop control and reaches the stable casting level at t_6.

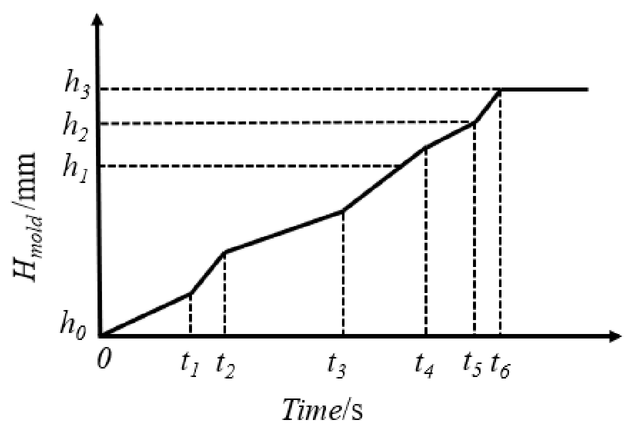

Fig. 3. The target liquid level curve of the mold

The sensor of the liquid level in the mold cannot detect a level below h1 due to hardware limitation and high-temperature steam, so it is necessary to establish a relational model between the stopper rod opening degree and the liquid steel outflow velocity and calculate the stopper rod opening degree at different stages of casting according to

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the model. Then, the stopper rod opening degree sequence is put into the first-level system (i.e., direct control system of continuous casting machine) of the production line to realize automatic casting.

Equation (1) is the model of the liquid level variation in the mold.

$$\begin{cases} Q_{in} = F(p) \\ \frac{dH}{dt} = \frac{Q_{in} - Q_{err}}{S} \end{cases} \quad (1)$$

Qin normal inflow of liquid steel in the mold

p stopper rod opening degree

F relationship between p and Qin

H liquid level in the mold

Qerr fluctuation of liquid steel in the mold under interference

S cross-sectional area of the billet.

In order to establish the relationship F between the stopper rod opening degree p and the liquid steel inflow Qin , this paper used the historical casting data of a steel mill to calculate the weight change relationship between the ladle and the tundish in the casting process, as shown in Equation (2) and indirectly established the relationship F according to the law of mass conservation. Specifically, the liquid steel in the ladle flows into the tundish at uniform velocity trough the fixed opening degree water outlet, and the liquid steel in the tundish flows into the mold at a nonuniform velocity through the stopper rod control. The liquid level in the mold rises gradually. The sensor sampling interval for stopper rod opening degree in association with the weight of the ladle and the tundish was 0.5 s. According to the law of conservation of mass, the difference between the decrease in the weight of the ladle and the increase in the weight of the tundish every 0.5 s is the weight of the liquid steel flowing into the mold from the tundish at that stopper rod opening degree.

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$$\begin{cases} \Delta W_{big} = W_{big}^{t} - W_{big}^{t+1} \\ \Delta W_{mid} = W_{mid}^{t+1} - W_{mid}^{t} \\ s.t. \Delta W_{big} > \Delta W_{mid} > 0 \\ Q_{in} = \frac{\Delta W_{big} - \Delta W_{mid}}{\rho} \\ p \to Q_{in} \end{cases} \quad (2)$$

Wbig weight of liquid steel in the ladle

Wmid weight of liquid steel in the tundish

ρ density of the liquid steel

Considering the weight of the liquid steel in the tundish also affects the flow velocity at outlet of stopper rod, the heavier the liquid steel is, the faster the outflow velocity of the liquid steel can be under the same stopper rod opening degree. Therefore, in order to model the actual casting situation more accurately, the parameter of the tundish weight was introduced based on Equation (1), and the correction coefficient k was added, which was determined by fitting with the historical data. The final equation of liquid level variation in the mold is shown in Equation (3).

$$\frac{dH}{dt} = \frac{Q_{in}(t) \cdot W_{mid}^{t} \cdot k^{-1} - Q_{err}(t)}{S} \quad (3)$$

A shown in Equation (3), assuming the opening degree of stopper rod at time t is p, the volum of liquid steel flowing into the mold from tundish Qin can be calculated according to Equation (2) under this stopper rod opening. W_{mid}^{t} wight of liquid steel in the tundish at time t, which can be directly obtained from the detection data of t he weight sensor. Qerr refers to the fluctuating volume of liquid steel in the mold caused by environmental interference at time t, wich is usually complicated and difficult to predict in real casting. The purpose of setting W_{mid}^{t} in this paper was only to verify the robustness of the proposed method, so its specific value was manually set. When solving Equation (3), an initial value of k was first given, and then the change of the liquid level in the mold dH was constantly calculated until the end of the casting. The liquid level in the mold was recorded at this time and compared with the value detected by the sensor of liquid level in the mold. If the difference is large, it indicates that the value of k is unreasonable. The value of k was constantly adjusted until the difference was within the allowable range. At this time, Equation (3) can simulate the change process of the liquid level in the mold in the casting process and solve the problem that the sensor of liquid level in the mold cannot work normally in the first stage.

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AUTOMATIC CASTING CONTROL METHOD

REINFORCEMENT LEARNING MODELING

Reinforcement learning is the product of combining cognitive science and computational intelligence. By interacting with the environment to learn knowledge, the agent can effectively explore the high-dimensional continuous space and finally make decisions. To clearly characterize the interaction process, reinforcement learning introduces the Markov Decision Process (MDP), which involves three basic elements: state, action and reward. In this paper, an MDP model was established for the automatic casting control problem, as shown in Fig. 4.

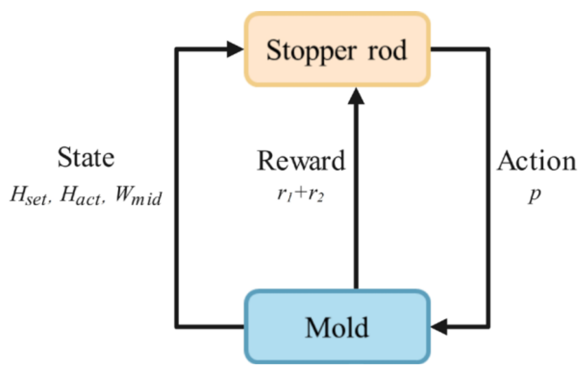

Fig. 4. Automatic casting control MDP model

In order to use the reinforcement learning algorithm, the state space, action space and reward function of automatic casting control were defined in detail based on the MDP model. State space S = {s = [Hset, Hact, Wmid]}, where Hset, Hact and Wmid represent the target liquid level in the mold, the actual liquid level in the mold and the weight of the tundish, respectively.

Action space A = {a = [p]}, where p represents the stopper rod opening degree, which can be any value in the range of 0–30 mm, p = 0 indicates that the stopper rod is not opened, and the liquid steel in the tundish cannot flow into the mold, p = 30 indicates that the stopper rod is fully opened, and the liquid steel in the tundish can flow into the mold at full speed. Reward function R = {r = [r1 + r2]}, where r1 is 0 or 1, indicating the reward obtained by the agent at the end of the control task, r1 = 1 indicates that the agent has completed the task, that is, the stopper rod successfully

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controls the liquid level in the mold to reach the starting level. In other cases, r1 = 0 will be given. r2 represents the real-time reward obtained by the agent during the control process, which is related to the liquid level error Herr = Hset - Hact in the mold. The specific calculation equation is shown in Equation (4).

$$r_2 = \begin{cases} 1, H_{err} \leq 1 \\ 0.1, 1 < H_{err} \leq 5 \\ -0.5, 5 < H_{err} \leq 10 \\ -1, H_{err} \geq 10 \end{cases} \quad (4)$$

For the final result of control it is extremly important to select an appropriate reinforcement learning algorithm. The steel level of the mold in continuous casters is affected by nonlinearities and disturbances, such as bulging, stopper rod and mold vibration, valve erosion, argon injection, and clogging/unclogging [8], so the robustness and generalization ability of the strategy must be hight. The SAC uses a stochastic strategy instead of a deterministic strategy [9] and greatly improves exploration efficiency and training stability by introducing a maximum-entropy objective [10]. Moreover, it is less sensitive to hyperparameters, so the SAC was chosen as the core algorithm of the model.

The state space of the automatic casting control task is a three-dimensional vector, and the dimension is small. In this paper, the policy network and the critic network of the algorithm use a multilayer, fully connected neural network. The input of the policy network is the state, and the output is the action probability distribution function [11]. The input of the critic network is the state, and the output is the value of the state. The optimal number of hidden layers and neurons was selected through experiments. A rectified linear unit (ReLU) was used as the activation function.

IMPROVED SAC ALGORITHM

The SAC algorithm uses an experience replay mechanism to cache all samples generated by the agent during exploration in the experience pool, including the samples of liquid level fluctuation or stability in the mold and the samples of the stopper rod opening degree vibration or stability. By default, all samples have the same weight [12], and samples are extracted from the experience pool in a completely random way to train the network. However, these samples have different influences on the network training process. The random method ignores the importance and differences of the samples. Therefore, this paper proposes to introduce an additional Heterogeneous Experience Pool (HEP) to cache the samples of the stopper rod opening degree oscilation, in order to enhance network training using such samples to reduce unnecessary oscilation during the stopper rod movement, thus improving the stability of the continuous casting production. This algorithm is named HEP-SAC in this paper, and its pseudocode is shown in Algorithm 1.

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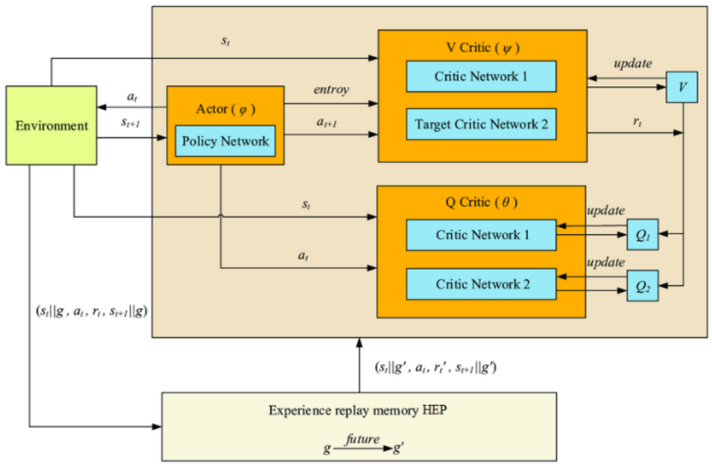

Fig. 5. Network structure of the HEP-SAC algorithm

Algorithm 1. Automatic casting control algorithm based on HEP-SAC

Input: billet width, billet thickness, target liquid level curve.

Output: neural network parameters.

Initialize the experience pool and set the minibatch size.

Initialize the parameters of the neural network.

for each iteration, do

for each environment step, do

generate action at based on state st.

execute action at, generate sample x1 = {st, at, rt, st+1}.

store x1 in the default experience pool.

calculate the oscilation amplitude of the stopper rod

Rs = at – at-1 .

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if Rs > threshold value,

store x2 = [{st-1, at-1, rt-1, st}{st, at, rt, st+1}]

in the HEP.

end if

end for

N1 = minibatch $\cdot \eta \cdot 2^{-1}$

N2 = minibatch_(1 - η)

if x2 quantity > N1 and x1 quantity > N2

for each gradient step, do

sampling from HEP and default experience pool.

update neural network parameters.

end for

end if

end for

4. EXPERIMENT AND ANALYSIS

Experiment Environment and Parameter Setting

In this paper to verify the availability of the relational model between the stopper rod opening degree and the liquid steel outflow velocity, Magma software was used to establish the fluid domain related to the stopper rod in a continuous casting machine. Magma also was used to realise the whole process of numerical simulation, including the establishment of the model and the grid, the setting of the boundary conditions the visualization of the results.

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Figure 6. Three-dimensional model diagram of the fluid domain

The Application Programming Interface (API) provided by OPenAI Gym was used to implement the environment function.

The TensorFlow framework was used to implement the reinforcement learning algorithm.

The algorithm and environment interacts to complete the training.

Software configuration related to the training platform are shown in Table 1.

Table 1. The detailed configurations of software

Software	Configuration
Operating System	Windows 11
IDE	PyCharm 2021
Pyton	3.6.2
TensorFlow	2.1.0
Gym	0.21.0

For training and learning is important the environment of reinforcement learning [13]. The environment settings in the MDP model included the following:

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The billet width was 1540 mm, and the billet thickness was 230 mm.

The rising process of the target liquid level in the mold included five stages, and the liquid level reached the target height at a uniform speed within the specified time window of each stage. The duration of the five stages was 7 s, 3 s, 20 s, 20 s and 25 s, respectively. The rise of the liquid steel level in the five stages was 30 mm, 20 mm, 200 mm, 64 mm and 100 mm, respectively. In order to verify the performance of the HEP-SAC algorithm, this paper compares it with the Twin-Delayed Deep Deterministic Policy Gradient (TD3) and the SAC algorithm, and analyzes its training performance and control performance.

The same hyperparameters of all algorithms included the following:

-number of training rounds was 350

-number of steps in each round was 150

-batch size was 128

-number exploration steps was 1000

-number of network updates was 3

-learning rate was 3 x 10-4

-discount factor was 0.95

-size of the default experience pool was 5 x 105.

The unique hyperparameter settings of each algorithm are shown in Table 2.

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Table 2. The hyperparameters of each algorithm.

Parameter	TD3	SAC	HEP-SAC
Exploring noise standard deviation	0.3	-	-
Policy noise standard deviation	0.4	-	-
Delay update frecuency	3.0	-	-
Size of HEP	-	-	1 x 106
Sampling ratio	-	-	0.2

The HEP-SAC algorithm uses an additional HEP to cache two ordinary samples at adjacent time steps, so the size of the HEP should be twice that of the original experience pool to prevent sample overflow. The sampling ratio between the HEP and the original experience pool should be determined by experimentation. A large η can lead to a large number of oscilation samples collected and reduce the training of the neural network for the accurate liquid level samples, and a small η cannot meet the training of the neural network for the oscilation samples. All other parameters of the HEP-SAC algorithm should be the same as in the original SAC algorithm.

In order to quantify the performance of the control framework, two evaluation indexes were set in this paper, namely Automatic Casting Probability (ACP) and Stable Stopper Rod Opening Degree Probability (SSP). The specific calculation is shown in Equation (5). ACP was used to measure the deviation between the liquid level in the mold and the target liquid level curve. The moment when the liquid level error is within the set threshold is called the accurate liquid level moment. The proportion of the accurate liquid level moments in the total casting time is the ACP of the framework under the current casting task. The SSP was used to measure the stability of the stopper rod in the process of movement. The moment when the vibration amplitude of the stopper rod is within the set threshold is called the

stable opening degree moment. The proportion of the stable opening degree moment in the total casting time is the SSP of the framework under the current casting task.

$$\begin{cases} ACP = \frac{\sum_{i=0}^{T} H_{err}(t)<2}{T} \\ SSP = \frac{\sum_{i=0}^{T} R_s(t)<3}{T} \end{cases} \quad (5)$$

As shown in Equation (5), Herr is the liquid level error in the mold, T is the time steps of the automatic casting and Rs is the oscilation amplitude of the stopper rod. The smaller the ACP is, the more the liquid level in the mold deviates

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from the target liquid level curve, which not only easily causes slag inclusion, and thus affects the quality of billet, but also easily causes steel overflow, and thus poses a safety threat to the workers on site. The smaller the SSP is, the more unnecessary vibration exists in the opening degree sequence of stopper rod, which can easily cause irreversible structural loss to the equipment. Therefore, the larger the two evaluation indexes, the better performance of the control framework.

4.2. Availability Analysis of the Stopper Rod Flow Control Model

Fig. 7 shows the level fitting results of the relational model between the stopper rod opening degree and the liquid steel outflow velocity under different k, where the height of the mold was 900 mm and the insertion depth of the pulling machine was 350 mm. If a position is set indicating that the liquid level in the mold is 0 and this position is 200 mm from the top of the mold, the simulated level changes from -350 mm, and the level enters the effective detection range of the sensor at about 95 s. The error between the simulated level and the detected level can be controlled to within $\pm$5 mm until 110 s. Compared with the total increase in the level, the ratio is less than 2%, so the relational model proposed in this paper can meet the accuracy requirements. Considering the complexity of the liquid steel flow and the diversity of external disturbances, the value of k is suggested to be in the range of 300–310.

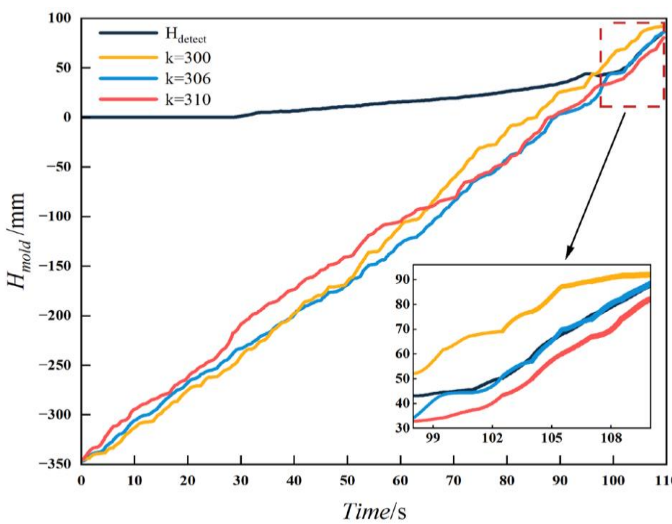

Fig. 7. Simulated liquid level in the mold at different k.

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4.3. Convergence Performance Analysis of HEP-SAC Algorithm

Fig. 8 shows the training process of TD3, SAC and HEP-SAC under the same set of random seeds. It can be seen that TD3 algorithm had the fastest learning speed, but the reward value after convergence was the lowest. This is because the deterministic strategy easily causes agents to fall into the overfitting state. The convergence speed and final performance of the HEP-SAC algorithm exceeded that of the baseline algorithms. It shows that the samples stored in the HEP can guide the training of neural networks correctly.

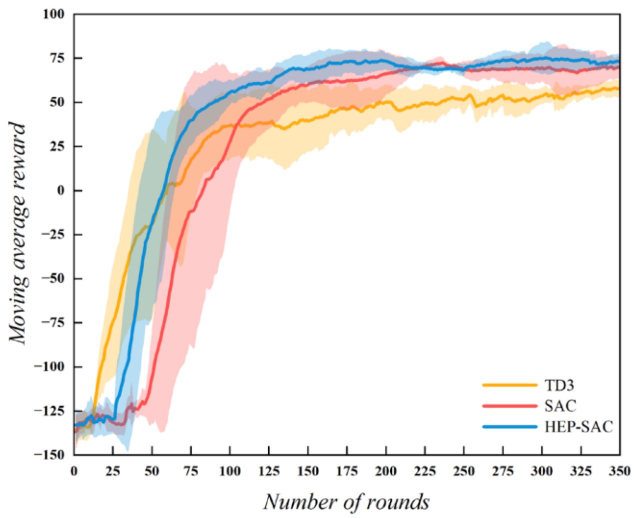

Figure 8. Training process diagram of different algorithms

4.4. Performance Analysis of Control Based on HEP-SAC

The performance of the control framework was mainly verified by ACP and SSP. The specification of the billet was set as 1540 mm x 230 mm, and two different types of perturbations were added: the first was the sudden rise of the liquid level in the mold at 15 s, and the second was the sudden drop of the liquid level in the mold at 45 s. The level change caused by both disturbances was set at 20 mm to verify the robustness of the control framework. Fig. 9a,b shows the time-varying curves of the liquid level error in the mold and the stopper rod opening degree in this task. It can be seen that the proposed method had a smaller liquid level error in the mold and a more stable control sequence under normal and disturbed conditions, and its performance exceeded that of the baseline algorithms.

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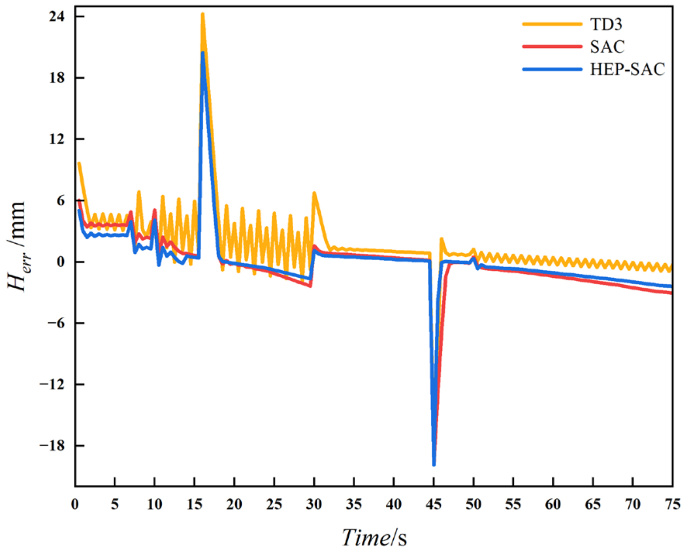

Figure 9.(a) Curves of the liquid level error in the mold

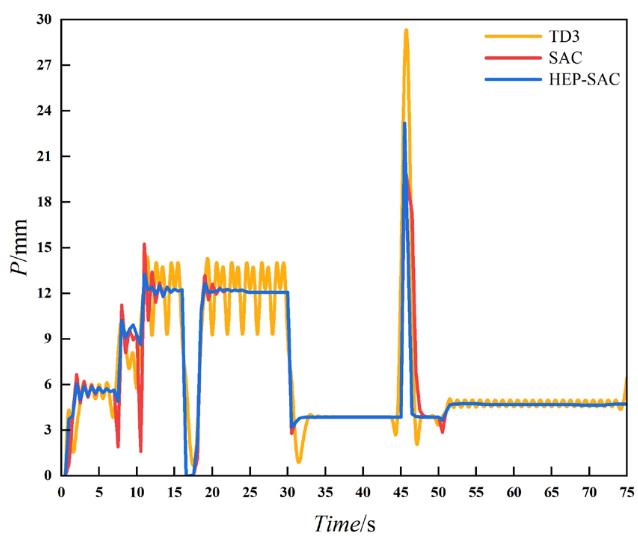

Figure 9.(b) Curves of the stopper rod opening degree

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The performance quantification results of the control framework are shown in Tables 3 and 4. Different billet widths were set, and the billet thickness was uniformly set at 230 mm. The results show that the ACP of the proposed method reached more than 80% under different casting tasks, and the control accuracy improved by 4.29% on average compared with the baseline algorithms. The SSP reached more than 75%, and the control stability improved by 3.17% on average compared with the baseline algorithms.

Table 3. ACP of each algorithm in different casting tasks

Width/mm	No Disturbance		
	TD3	SAC	HEP-SAC
1100	72.3	82.6	85.2
1200	79.5	83.2	86.7
1300	81.3	91.7	96.6
1400	83.7	90.3	94.4
1540	80.6	86.7	92.5
1640	76.5	83.7	89.4
Width/mm	Added Disturbance		
	TD3	SAC	HEP-SAC
1100	68.2	78.7	81.3
1200	70.3	77.5	82.5
1300	76.5	87.2	91.8
1400	79.4	86.1	89.4
1540	76.6	79.7	86.5
1640	72.3	74.6	84.2

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Table 4. SSP of each algorithm in different casting tasks

Width/mm	No Disturbance		
	TD3	SAC	HEP-SAC
1100	68.6	85.9	89.1
1200	70.1	90.2	93.5
1300	66.8	89.6	93.8
1400	72.2	91.9	94.4
1540	74.3	86.4	90.0
1640	65.2	91.1	95.3
Width/mm	Added Disturbance		
	TD3	SAC	HEP-SAC
1100	61.7	74.7	78.4
1200	63.1	81.3	85.0
1300	60.1	80.0	84.4
1400	65.0	82.7	86.8
1540	67.0	77.8	79.0
1640	58.7	82.0	85.2

CONCLUSIONS

In this paper by modeling the automatic casting problem as the MDP model, reinforcement learning was used to establish the stopper rod opening degree control framework, and an HEP was introduced to improve the experience replay mechanism of the SAC algorithm.

INTERNATIONAL JOURNAL OF APPLIED RESEARCH AND TECHNOLOGY
ISSN 2519-5115
IJART- Vol-9, Issue-2, April, 2024
Available Online at http://www.ijart.info/
DOI: https://doi.org./10.24163/ijart/2017/9(2):51-69

The experimental results show that the convergence speed and performance of the HEP-SAC algorithm exceeded that of TD3 and SAC algorithm. Compared with the control framework based on baseline algorithms, the framework based on HEP-SAC improved the accuracy of the liquid level in the mold by 4.29% and the stability of the stopper rod opening degree by 3.17%, which shows the effectiveness of the improved method in this paper. With the development of sensors and other hardware equipment, it will be possible to establish a more accurate relational model between the stopper rod opening degree and the liquid steel outflow velocity, so as to improve the reliability of the reinforcement learning control framework and promote the continuous progress of automatic casting technology.

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