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Human-on-the-Loop Control in Surface Mount Technology via Deep Reinforcement Learning

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ABSTRACT

Considering the importance of solder paste printing in the production process of surface mounted technology (SMT), as well as the decisive impact of key process parameters on the solder paste printing effect. Traditional methods, whether manual or machine tuning, suffer from significant production capacity losses due to long downtime, and machines cannot adaptively adjust parameters based on human expert knowledge, thereby affecting the qualification rate of solder paste printing and the efficiency of SMT production lines. This paper proposes a human–machine integration optimization method for key printing process parameters. By establishing a printing quality prediction model and a key process parameter strategy model, a closed-loop control system has been formed to achieve machine autonomous parameter tuning with expert knowledge. And this paper has completed the establishment of the strategy model based on deep reinforcement learning methods, enabling the SMT production line to predict and adjust key process parameters in real time based on SPI data. In addition, the optimization method described in this paper retains the final decision-making authority of human operators to ensure emergency correction of prediction bias and decision failure history in the system. The final experimental results of this paper indicate that the proposed optimization method performs well in terms of qualification rate, correction effect, SPI data prediction, etc. These demonstrate the effectiveness and value of the proposed human-on-the-loop optimization method in SMT production lines.

1 | Introduction

Surface mount technology (SMT) [1–3] involves installing surface mount components on printed circuit boards through reflow or immersion soldering. Traditional solder paste printing methods [4–6] in SMT rely heavily on manual experience for parameter adjustment, leading to significant downtime and high costs. The existing manual tuning strategy requires extensive experiments on the production line, consuming substantial resources and resulting in substantial capacity loss. This traditional approach has strong human dependence and lacks predictive performance [7–10]. It overemphasizes human experience, failing to fully utilize machine learning from large datasets. If the solder paste printing test fails, production is halted, and the machine cannot self-adjust parameters. Additionally, the production line cannot predict the solder paste inspection (SPI) data [11, 12] generated by the process parameters, negatively impacting production efficiency and qualification rates.

In order to solve the above-mentioned problems in traditional manual parameter tuning, in recent years, relevant fields have continuously attempted to explore the use of artificial intelligence methods [13–15]. Existing AI methods focus on optimizing machine decision-making algorithms but often fail to fully utilize human expertise. For example, literature [14] developed optimization models for surface mount technology component

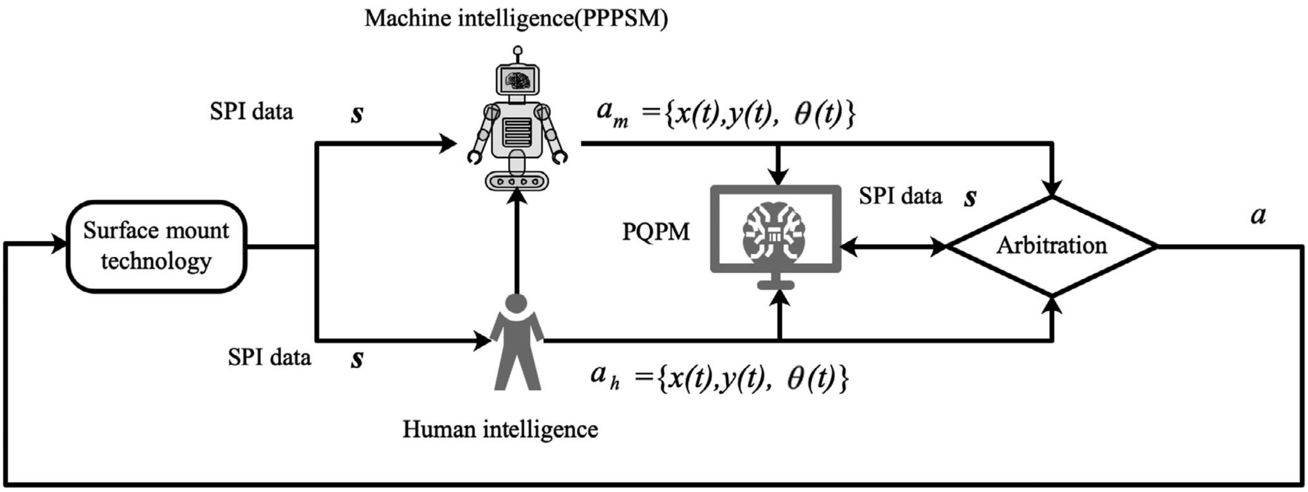


FIGURE 1 | Human-on-the-loop optimization framework in surface mount technology.

systems based on adaptive evolutionary strategy search (AESS) and segmented particle swarm optimization (SPSO) to maintain the quality of printed circuit boards (PCBs). Reference [15] designed an optimization model for SMT machines based on gradient boosting regression, K-nearest neighbor regression, and multi evaluation and output to the mount. For different solder paste volume coverage, reference [16] studied a novel mixed integer nonlinear programming (MINLP) model to optimize printing parameters for different PCB pad configurations. Literature [17–19] attempted to use reinforcement learning related methods for data mining and algorithm optimization to achieve the goal of adaptive adjustment of process parameters in printed circuit board surface mounting technology. However, the above related work focuses on optimizing machine decision-making algorithms, and once the machine decision-making subject collapses, they can only seek help from human experts through shutdown and production. Based on artificial intelligence methods, can human operators be placed on the loop when building the entire SMT production line closed-loop control system, thus forming a human–machine integration optimization method? This is the direction we are thinking about.

This paper proposes an optimization method for key process parameters of SMT production line based on human–machine integration to improve the efficiency and qualification rate of solder paste printing, as shown in Figure 1, addressing the existing technical issues mentioned above. This paper introduces deep reinforcement learning for the generation of key process parameters in solder paste printing, combined with a printing quality prediction model, to form a system for optimizing key process parameters in printing, which has good autonomy and can adapt to complex situations such as multi-step prediction. The key process parameters of the SMT production line in this paper are given by AI intelligent decision-making. However, in case of sudden situations where AI intelligent decision-making cannot solve the problem of printing non-compliance in a short period of time, human experts can quickly correct the key process parameters based on their own experience and knowledge. Specifically, the contribution points are as follows:

- **Human–Machine Integration Optimization Method**: we propose a novel human–machine integration optimization method for key printing process parameters in surface mount technology (SMT). This method combines human expertise with AI decision-making to form a closed-loop control system, achieving autonomous parameter tuning with expert knowledge.
- **Deep Reinforcement Learning Application**: we introduce deep reinforcement learning for generating key process parameters in solder paste printing, combined with a printing quality prediction model. This system not only improves the autonomy of parameter optimization, but also adapts to complex situations such as multi-step prediction.
- **Human Final Decision-Making Authority**: our method retains the final decision-making authority of human operators, ensuring that they can quickly correct key process parameters based on their experience and knowledge when AI decision-making encounters issues. This design enhances the flexibility and reliability of the system.

The rest of this paper is arranged as follows. Section 2 provides a problem description and discusses related work. Section 3 provides a detailed explanation of the main framework and methods of the paper. Section 4 verifies the effectiveness of the proposed method, and Section 5 summarizes the work of this paper.

2 | Problem Description and Related Work

2.1 | SMT Model Establishment

Considering that the pass rate of solder paste printing is determined by key process parameters, this paper establishes a strategy model for generating key process parameter models based on deep reinforcement learning methods. This problem can be modeled as follows:

State: $s(t) = \{height(t), area(t), volume(t), offset_x(t), offset_y(t)\}$, where $height(t)$ represents the printing height of solder paste, $area(t)$ is the printing area, $volume(t)$ is the printing volume, $offset_x(t)$ is the printing offset in the x direction, and $offset_y(t)$ is the printing offset in the y direction.

Action: $a(t) = \{x(t), y(t), \theta(t)\}$, where $x(t)$ represents the first parameter in the key process parameters, which is the parameter configuration in the x direction, $y(t)$ represents the second parameter in the key process parameters, which is the parameter configuration in the y direction, and $\theta(t)$ represents the third parameter in the key process parameters, which is the parameter configuration on the angle.

Reward: $r(t) = -\sqrt{offset_x(t)^2 + offset_y(t))^2}$, The reward for setting the model is closely related to the $offset_x(t), offset_y(t)$ in the state variables $s(t)$, which depends on the evaluation criteria for whether the solder paste printing inspection is qualified.

Therefore, based on the Bellman equation [20], a state action value function is constructed:

$$\begin{aligned} Q(s(t), a(t)) &= Q(s(t), \mu(s(t)|\delta^{\mu})|\delta^{Q}) \\ &= r(s(t), a(t)) + \gamma Q'(s(t+1), a(t+1)) \\ &= r(s(t), a(t)) + \gamma Q'(s(t+1), \mu'(s(t+1)|\delta^{\mu'}))|\delta^{Q'}) \end{aligned} \tag{1}$$

Among them, $Q(\cdot)$ and $Q'(\cdot)$ represent the action value functions at time t and time $t+1$, γ is the discount factor, $\mu(\cdot)$ and $\mu'(\cdot)$ represent the policy function. δ^{μ} is parameter of the policy function μ, and δ^{Q} is parameter of the value function Q. By continuously optimizing the equation, the strategy function that generates key process parameters is continuously optimized, ultimately achieving the goal of machine intelligence self adjusting the solder paste printing process parameters in the SMT production line.

The human on-the-loop [21, 22] optimization programme involves collecting human experts to manually set the key process parameters $\{x(t), y(t), \theta(t)\}$ of the SMT production line based on empirical knowledge. Based on the SPI data of solder paste detection generated by experts configuring key process parameters on the production line, this paper uses a neural network to fit the corresponding relationship between the key process parameters and SPI data. This model is the printing quality model $P^m(\cdot)$ described in Section 3, which learns the operational experience of human experts through the form of humans on the loop. And the input-output relationship of the model is as follows:

$$\begin{aligned} &\{height(t), area(t), volume(t), offset_x(t), offset_y(t)\} \\ &= P^m(x(t), y(t), \theta(t)) \end{aligned} \tag{2}$$

In the above equation, the left side of the equal sign represents the state element $s(t)$ in the reinforcement learning based strategy model mentioned above, and the right side of the equal sign represents the action element $a(t)$ in the strategy model mentioned above. In other words, this paper completes the human–machine integration optimization scheme in the SMT field by establishing two models, namely the key process parameter model for solder paste printing and the solder paste printing quality prediction model. In addition, the key printing process parameters in the optimization plan described in this paper are usually given by AI intelligent decision-making. In case of sudden situations where AI intelligent decision-making cannot solve the problem of printing non-compliance in a short period of time, the human experts can also quickly correct the key process parameters based on their own experience and knowledge.

2.2 | Related Work

SMT production line is one of the key processes in modern electronic manufacturing, involving precise positioning, mounting, welding and other steps of electronic components. The setting of key process parameters is crucial for production efficiency, quality, and reliability in SMT production lines.

Solder paste printing in SMT has received widespread attention [14, 23–27], especially with the exploration of artificial intelligence methods [13–15]. Reference [23] developed an online dynamic prediction model for real-time stencil printing process state prediction, which helps with real-time decision-making in the stencil printing process by maintaining high prediction accuracy. Reference [25] is a review of machine learning optimization methods that may be involved in the field of surface mounted electronic assembly technology, including artificial neural networks, support vector machines, convolutional neural networks, K-nearest neighbors, etc. The literature [13] develops a machine learning model based on support vector regression (SVR) and neural networks (NN) to analyze and predict the movement and rotation of components in the xx and yy directions during reflow, which involves revealing the relationship between self alignment and various variables, including component geometry, pad geometry, etc. Reference [28] studied a fuzzy architecture to evaluate quantitative and precise indicators of welding interconnect quality by replicating the work of human experts in the evaluation process, which involves a feature extraction block and two fuzzy blocks. Reference [14] uses random forest regression (RFR) and artificial neural networks (ANN), as well as adaptive evolutionary strategy search (AESS) and segmented particle swarm optimization (SPSO), to develop a series of optimization models for surface mount technology (SMTA) systems to maintain the quality of printed circuit boards (PCBs). Reference [26] applies convolutional neural networks for early detection of solder paste defects on high-performance PCBs, thereby solving the problem of low production efficiency in defect detection during the final production stage. Reference [27] studied a mathematical programming model that can be used to support key decisions related to production planning and control of surface mount technology production lines in specific environments. Reference [15] proposed a surface mount machine optimization model (MOM), which includes gradient boosting regression, K-nearest neighbor regression to predict the position of components after reflow process, and optimizing the placement parameters through multi evaluation and output to the mount.

Reference [29] developed a machine learning model by analyzing algorithms such as RFR, SVR, NN, gradient boosting (GB), and K-nearest neighbor (KNN) to predict component self alignment offsets along component length, width, and angle directions. Reference [30] uses SVR models (involving two kernel functions, SVR linear and radial basis function [SVR RBF]) to predict component offsets under different conditions based on solder paste and placement settings. Reference [31] is based on

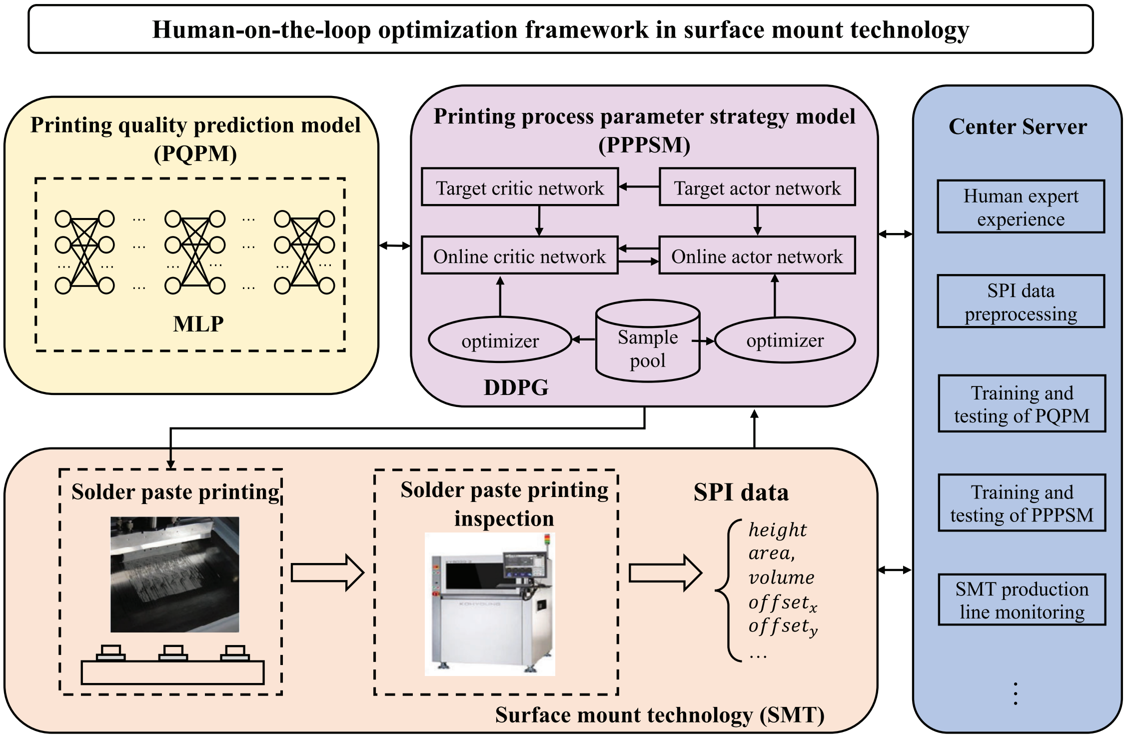


FIGURE 2 | The functional block diagram of human-on-the-loop optimization in surface mount technology.

the response surface method (RSM) experimental method, and establishes a predictive polynomial equation for the height, area, and volume of printing solder paste based on important solid paste stencil printing (SPSP) parameters. It plays an important role in quickly predicting the optimal printing parameters during the parameter setting process, thereby improving production efficiency and quality. Reference [16] studied a novel MINLP model [32] for optimizing printing parameters of different PCB pad configurations for different solder paste volume covers. References [17, 18] use Q-learning reinforcement learning method to adaptively adjust the process parameters of silk screen printing process in printed circuit board surface mounting technology online. Reference [19] conducted data mining on SMT production lines and developed an optimization system for SMT production quality control system using decision tree algorithm and AdaBoost reinforcement learning machine algorithm. The generation of key process parameters for SMT production lines can be used as a decision problem solution, while reinforcement learning focuses on how agents take different actions in the environment to maximize cumulative rewards. Therefore, the process of finding the optimal strategy by solving reinforcement learning problems is the process of optimizing the key process parameters of the SMT production line involved in this paper.

3 | Main Methods

This paper develops a closed-loop system for optimizing key process parameters in SMT production lines based on human–machine integration, which belongs to the field of shared control technology between humans and machines (artificial intelligence), as shown in Figure 2.

3.1 | Human-on-the-Loop Control in Surface Mount Technology

Consider the solution of human on circuit for SMT, as shown in Figures 1 and 2. Machine intelligence (printing process parameter strategy model [PPPSM]) autonomously adjusts key process parameters $a_m(t) = \{x(t), y(t), \theta(t)\}$ based on real-time SPI detection data $s(t) = \{height(t), area(t), volume(t), offset_x(t), offset_y(t)\}$ on the production line. When human intelligence intervenes in the decision-making system in a timely manner, it will also provide empirical values $a_h(t) = \{x(t), y(t), \theta(t)\}$ based on real-time $s(t)$. Both $a_m(t)$ and $a_h(t)$ will enter the intelligent prediction model (printing quality prediction model [PQPM]), and after prediction and arbitration, the final decision value $a(t)$ will be given.

PQPM (as described in Section 3.2) is used to fit the correspondence between key process parameters and SPI data. PPPSM (as described in Section 3.3) is used to train the strategy model between SPI data and key process parameter improvement. The human operator monitors the system's performance and can intervene at any point to correct or adjust the key process parameters based on their expertise and experience. The human operator's input is integrated into the system through a feedback loop, allowing the system to learn from human corrections and improve its future performance. This paper integrates expert experience and AI decision-making to form a closed-loop system between the printing quality prediction model and the printing process parameter strategy model. Real time adjustment of printing process parameters based on SPI data on the SMT production line to achieve the goal of improving qualification rate and production efficiency.

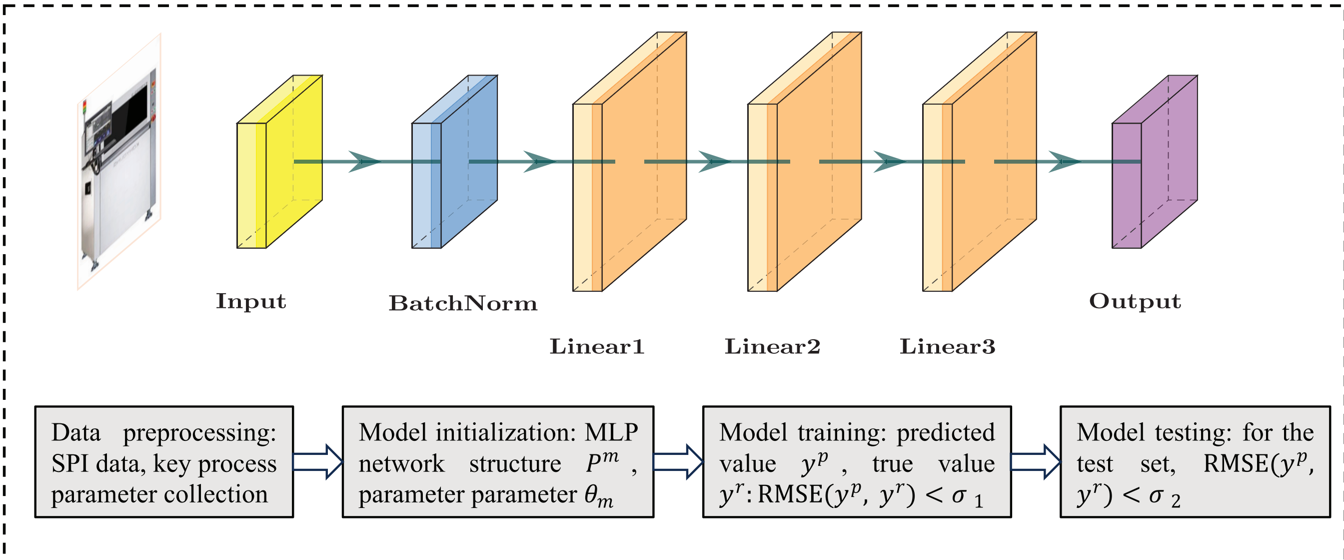


FIGURE 3 | Network structure of the printing quality prediction model (PQPM).

3.2 | Printing Quality Prediction Model

PQPM aims to establish and learn the correlation between key process parameters and SPI detection data. This model serves as a critical component in our human-on-the-loop optimization framework for SMT production lines. The primary goal of the PQPM is to accurately predict the solder paste printing quality based on the key process parameters. The model takes the process parameters $\{x, y, \theta\}$ as inputs and outputs the corresponding SPI detection data, including printing height, area, volume, and offsets. By establishing this relationship, the PQPM enables real-time prediction of printing quality, facilitating proactive adjustments to the process parameters and enhancing overall production efficiency. The PQPM is implemented using a multi-layer perceptron (MLP) neural network. The MLP consists of multiple layers, including input, hidden, and output layers, as shown in Figure 3. The architecture is designed to capture the complex nonlinear relationships between the process parameters and the SPI detection data. By optimizing the PQPM, we aim to achieve a robust and accurate prediction model that can support real-time decision-making in SMT production lines, thereby improving production efficiency and quality.

And the printing quality prediction model training algorithm is shown in the Algorithm 1. Suitable machine learning algorithms and model structures are selected for the training set for model training. Common machine learning algorithms include neural networks, support vector machines, and random forests. This paper uses a MLP network, randomly initializing the network structure P^m and parameters θ^m, with a training error of MSE, and iteratively iterating the MLP model parameters based on gradient descent method. First, we initialize the network structure and parameters θ^m of P^m, and collect the sample dataset D. During the training process, randomly retrieve N experience samples and calculate the difference (MSE) between the predicted output of the PQPM model and the true sample output. The model parameters are then updated based on gradient descent through backpropagation. This process continues until the model error reaches an acceptable threshold, resulting in a printing quality prediction model.

ALGORITHM 1 | Printing quality prediction model(PQPM) training algorithm.

Input: key process parameters $X = \{x, y, \theta\}$.

output: predicted SPI data
$Y = \{x, y, \theta, height, area, volume, offset_x, offset_y\}$.

Initialization: Initialize MLP network structure P^m and parameters θ; Collect and store process parameters related to solder paste detection and SPI detection data on the SMT production line: $D = \{X; Y\}$;

repeat

Randomly retrieve N sets of data from the experience pool D;

Based on gradient descent method, $mse(Y, P^m(X; \theta))$, fit and train PQPM with key process parameters $X = \{x, y, \theta\}$ as inputs and SPI detection data as outputs, while updating the model parameters θ;

until the printing quality prediction neural network PQPM can simulate solder paste printing results with tolerable errors, that is, $Y == P^m(X; \theta)$.

3.3 | Printing Process Parameter Strategy Model

PPPSM serves as the core component of our human-on-the-loop optimization framework for SMT production lines. Its primary function is to optimize key process parameters based on real-time SPI data, thereby enhancing the efficiency and qualification rate of solder paste printing. The PPPSM is designed based on the DDPG algorithm, which combines the benefits of both value-based and policy-based reinforcement learning methods. The

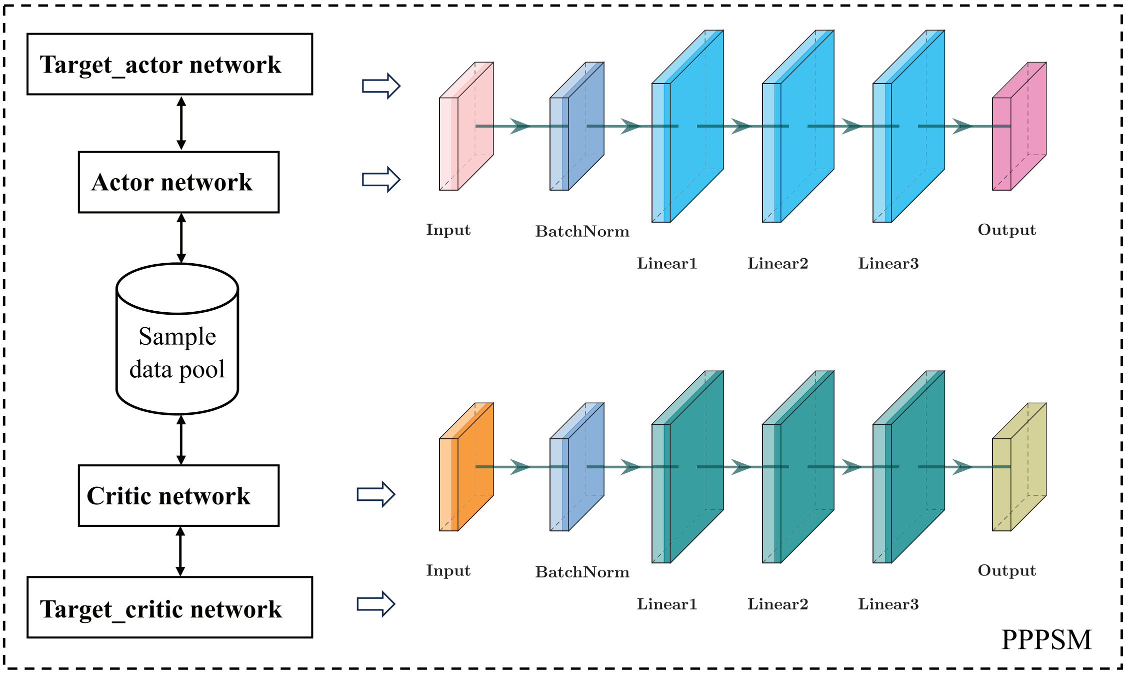


FIGURE 4 | Network structure of the printing process parameter strategy model (PPPSM).

components of the model are illustrated in Figure 4. Experience Replay Buffer stores historical data samples for efficient training and reduces the correlation between consecutive samples. Actor networks generate actions (key process parameters) based on the current state (SPI data). Critic network evaluate the actions generated by the actor network and provides feedback to optimize the policy. Target Networks stabilize the training process by providing a reference for the actor and critic networks. When establishing the objective function, it is necessary to weigh the relationship between different indicators based on the actual situation. The reward in the DDPG algorithm and the offset in the state variable $s(t)$ in this paper $Offset_x.Offset_y$ is closely related, that is, $r = -\sqrt{offset_x^2 + offset_y^2}$, in order to achieve a smaller tilt in solder paste printing, the better.

The algorithm for PPPSM is illustrated in the Algorithm 2. First, the network structure μ and parameters δ are initialized, and a sample dataset $D2$ is collected. In the early stage of model training, this paper uses a randomly initialized printing process parameter strategy network structure p^d and parameter θ^d, with a reward of r approaching 0 as a positive guidance, and iterates repeatedly. During training, experience samples are randomly retrieved from the dataset $D2$. The objective is to minimize r (the MSE between solder paste and components) by iteratively updating the model parameters δ of the strategy network. This process also involves incorporating human interventions as actions into the experience sample pool. The training continues until the closed-loop system formed by the PPPSM and the PQPM converges, resulting in a printing process parameter strategy model. In practical applications, model parameters can be continuously updated to improve the prediction accuracy of the model by monitoring printing quality data and production line status data.

ALGORITHM 2 | Printing process parameter strategy model (PPPSM) training algorithm.

Input: SPI data
$Y = \{x, y, \theta, height, area, volume, offset_x, offset_y\}$.

output: key process parameters $X = \{x, y, \theta\}$.

Initialization:Initialize DDPG network structure μ and parameters δ; Collect and store process parameters related to solder paste detection and SPI detection data on the SMT production line: $D2 = \{Y; X\}$; Set the reward function in DDPG: $r = -\sqrt{offset_x^2 + offset_y^2}$;

repeat

Randomly retrieve N2 sets of data from the experience pool $D2$;

With the goal of minimizing the offset between solder paste and components, iteratively update the strategy model parameters δ to maximize the reward value.
$X_m = \mu(Y; \delta); X_h = human - input; X = \{X_m, X_h\}$;

until when the trained PPPSM is combined with the PQPM to form a closed-loop control loop, the PPPSM strategy ($X_m = \mu(Y; \delta)$) converges and can ensure printing quality.

4 | Experimental Result

4.1 | Experimental Setup

The data resources for solder paste printing in this paper come from the actual production and testing data of a certain enterprise's production line. The original SPI data is nearly 1,000,000, with less than 400 printing process parameters, each containing 13 attributes. Figure 5 lists some data resources.

序号	X_Offset	Y_Offset	Theta_Offset	Height (um)	Area (um2)	Volume (um3)	Volume (%)	Area (%)	OffsetX(mm)	OffsetY(mm)	OffsetX(%)	OffsetY(%)
1	-0.221	-0.045	-0.018	118.422134517767	259155.80107868	31336851.5352157	120.535494923858	103.086691941624	0.01978807106599	0.0199397208121828	4.71695780456852	4.79040577411169
2	-0.221	-0.045	-0.018	118.422134517767	259155.80107868	31336851.5352157	120.535494923858	103.086691941624	0.01978807106599	0.0199397208121828	4.71695780456852	4.79040577411169
3	-0.221	-0.045	-0.018	118.422134517767	259155.80107868	31336851.5352157	120.535494923858	103.086691941624	0.01978807106599	0.0199397208121828	4.71695780456852	4.79040577411169

FIGURE 5 | Sample form of SPI data for SMT production line.

Here $\{Offset_x, Offset_y, Offset_\Theta\}$ represents the printing process parameters. These three values in the actual production line are preset by the operator into the printing machine panel based on their own experience. The printing machine is able to perform solder paste printing on circuit boards. In the traditional assembly line operation process, when the printed circuit board is detected as unqualified, it is necessary to manually adjust the printing machine parameters. Differently, this paper will use deep reinforcement learning methods combined with manual experience to generate printing process parameters.

Height (um) represents height, Area (um2) represents area, Volume (um3) represents volume, Volume (%) represents volume ratio, Area (%) represents area ratio, $Offset_x(mm)$ represents x-direction offset size, $Offset_y(mm)$ represents y-direction offset size, and $Offset_x(\%)$ represents x-direction offset percentage, and $Offset_y(\%)$ represents the percentage offset in the y-direction. The above nine attributes all belong to SPI detection data. The goal of the SMT production line is to maintain effective printing process parameters $(Offset_x, Offset_y, Offset_\theta)$. Thus, the offset during SPI data is infinitely close to 0. This paper will use neural networks to fit printing quality models, especially observing the fitting effects of $Offset_x$ and $Offset_y$ parameters. The training sample is Table 1. Among them, 5.31 Match SPI STAT-4.xlsx, 5.31 Match SPI STAT-5.xlsx, and 5.31 Match SPI STAT-6.xlsx represent the SPI data obtained during normal operation of the SMT production line. 5.31 Match SPI-STA-1.xlsx is the SPI data collected by changing $Offset_x \in [-0.3, 0.3]$. 5.31 Match SPI-STA-2.xlsx is the SPI data collected by changing $Offset_y \in [-0.3, 0.3]$. 5.31 Match SPI-STA-3.xlsx is the SPI data collected by changing $Offset_\theta \in [-0.2, 0.2]$.

TABLE 1 | SMT production line data classification annotation.

5.31-Match-SPI-STA-1.xlsx	SPI data corresponding to changes $Offset_x$ in process parameters $\{Offset_x, -0.032, -0.01\}$
5.31-Match-SPI-STA-2.xlsx	SPI data corresponding to changes $Offset_y$ in process parameters $\{-0.19, Offset_y, -0.01\}$
5.31-Match-SPI-STA-3.xlsx	SPI data corresponding to changes $Offset_\Theta$ in process parameters $\{-0.19, -0.032, Offset_\theta\}$
5.31-Match-SPI-STA-4.xlsx	SPI dataset for normal SMT production lines
5.31-Match-SPI-STA-5.xlsx	SPI dataset for normal SMT production lines
5.31-Match-SPI-STA-6.xlsx	SPI dataset for normal SMT production lines

4.2 | Training Results of Printing Quality Prediction Model

This paper aims to achieve closed-loop optimization design of solder paste printing detection and key printing process parameters on SMT production lines through human–machine integration. Before obtaining the printing process parameter strategy model, we first train the printing quality prediction model to obtain an accurate correspondence between key printing process parameters as inputs and SPI prediction data as outputs. The accuracy of this is based on the existing human operator configuration data and detection data on the production line as a reference. In other words, for the same key process parameters $\{x, y, \theta\}$, the predicted output of the printing quality prediction model should be as close as possible to the existing SPI data. The reward curve (Figure 6a) and loss curve (Figure 6b) for printing quality model training are shown in Figure 6. From Figure 6, it can be seen that the training process of the printing quality model based on Section 3.2 is convergent. In order to avoid the vanishing gradient caused by a small MSE at the beginning of the training phase, this paper multiplies the offset by 10, which is MSE multiplied by 100. Therefore, compared to the threshold of $0.1^2 = 0.01$, 0.0003 in Figure 6 is sufficient to meet the qualification criteria.

Figure 7 represents the offset in the x direction and the y direction of the SPI data predicted by the printing quality prediction model under different process parameters. Figure 7a shows the fitting of the first SPI data in the 5.31-Match-SPI-STA-1.xlsx dataset, where the red curve represents the true value and the blue asterisk represents the predicted output of the printing quality model. It is worth noting that considering the deviation of the true value 0.15 in the x direction, which seriously does not meet the production line qualification standards, a threshold upper limit

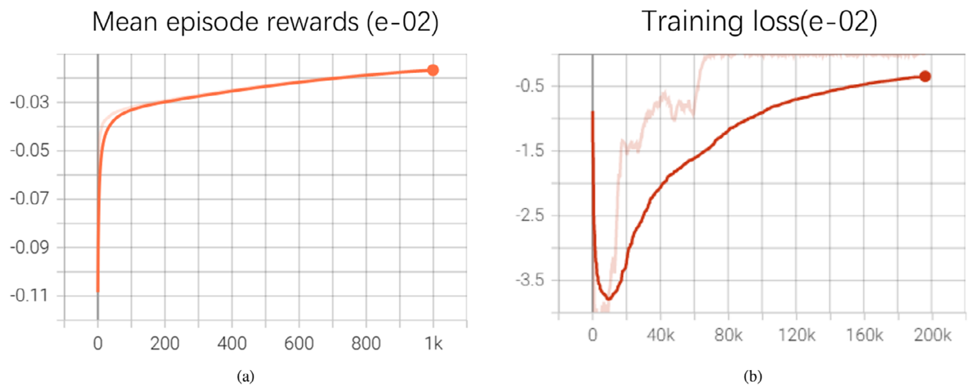


FIGURE 6 | (a) The rewards curve of training process for PQPM. (b) The loss curve of training process for PQPM.

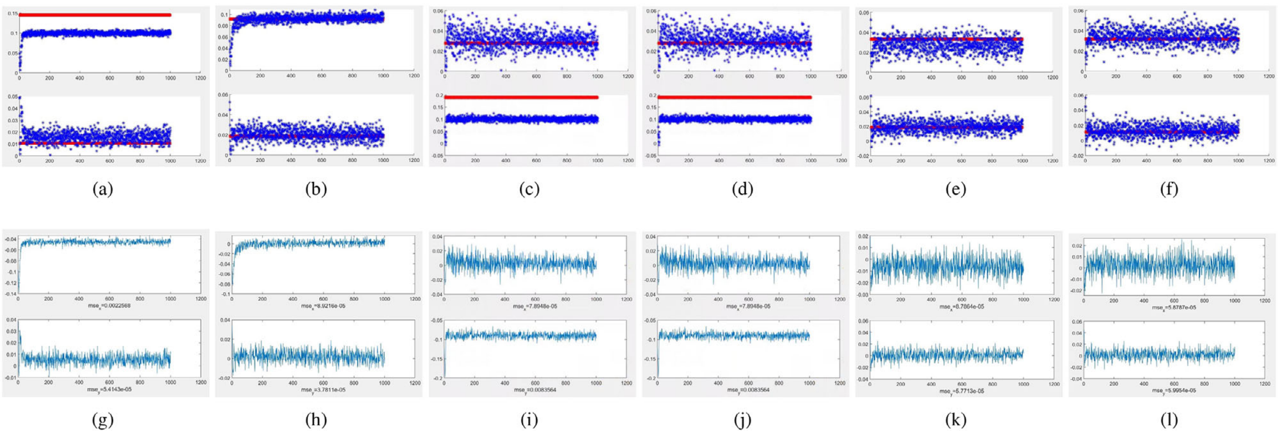


FIGURE 7 | (a) The predicted $offset_x$ and $offset_y$ of the first data in 5.31 Match SPI-STA-1.xlsx; (b) The predicted $offset_x$ and $offset_y$ of the second data in 5.31 Match SPI-STA-1.xlsx; (c) The predicted $offset_x$ and $offset_y$ of the first data in 5.31 Match SPI-STA-2.xlsx; (d) The predicted $offset_x$ and $offset_y$ of the second data in 5.31 Match SPI-STA-2.xlsx; (e) The predicted $offset_x$ and $offset_y$ of the first data in 5.31 Match SPI-STA-4.xlsx; (f) The predicted $offset_x$ and $offset_y$ of the second data in 5.31 Match SPI-STA-4.xlsx; (g) The $offset_x$ and $offset_y$ fitting error corresponding to (a); (h) The $offset_x$ and $offset_y$ fitting error corresponding to (b); (i) The $offset_x$ and $offset_y$ fitting error corresponding to (c); (j) The $offset_x$ and $offset_y$ fitting error corresponding to (d); (k) The $offset_x$ and $offset_y$ fitting error corresponding to (e); (l) The $offset_x$ and $offset_y$ fitting error corresponding to (f).

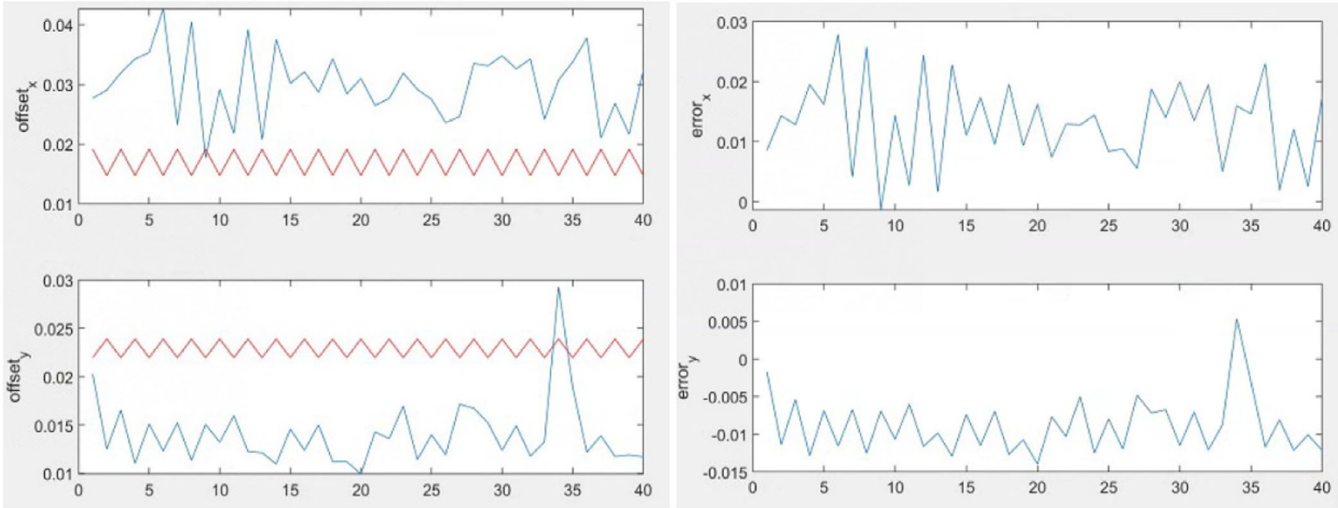
of 0.1 has been intentionally added to the predicted output of the printing quality model. Figure 7g shows the corresponding fitting error. $mse_x = 0.0023$ and $mse_y = 5.4143e-05$ represents the mean square error of the offset in the x direction and y direction in the SPI data, respectively. Figure 7b,h correspond to the fitting of the second SPI data in the 5.31 Match SPI-STA-1.xlsx dataset, as well as the mean square error of the offset in the x and y directions, respectively, and $mse_x = 8.9216e-05$ and $mse_y = 3.7811e-05$. Figure 7c,i correspond to the fitting of the first SPI data in the 5.31 Match SPI-STA-2.xlsx dataset, as well as the mean square error of the offset in the x and y directions, respectively, and $mse_x = 7.8948e-05$ and $mse_y = 0.0084$.

Figure 7d,j correspond to the fitting of the second SPI data in the 5.31 Match SPI-STA-2.xlsx dataset, as well as the mean square error of the offset in the x and y directions, respectively, and $mse_x = 7.0328e-05$ and $mse_y = 0.0069$. Figure 7e,k correspond to the fitting of the first SPI data in the 5.31 Match SPI-STA-4.xlsx dataset, as well as the mean square error of the offset in the x and y directions, respectively, and $mse_x = 8.7864e-05$ and $mse_y = 5.7713e-05$. Figure 7f,l correspond to the fitting of the second SPI data in the 5.31 Match SPI-STA-4.xlsx dataset, as well as the mean square error of the offset in the x and y directions, respectively, and $mse_x = 5.8787e-05$ and $mse_y = 5.9954e-05$.

Figure 8 shows the printing quality model testing effect. The red curve in Figure 8a represents the true value of SPI data, while the blue curve represents the SPI data predicted by the printing quality model. This paper selects 5.31-Match-SPI-STA-6.xlsx as the printing quality model test set. From Figure 8b, it can be seen that the deviation prediction of the PQPM model trained on multi-layer perceptrons in the x direction and y direction is small enough to differ from the true value of SPI data. $MSE = mse_x + mse_y = 4.4475e-4$.

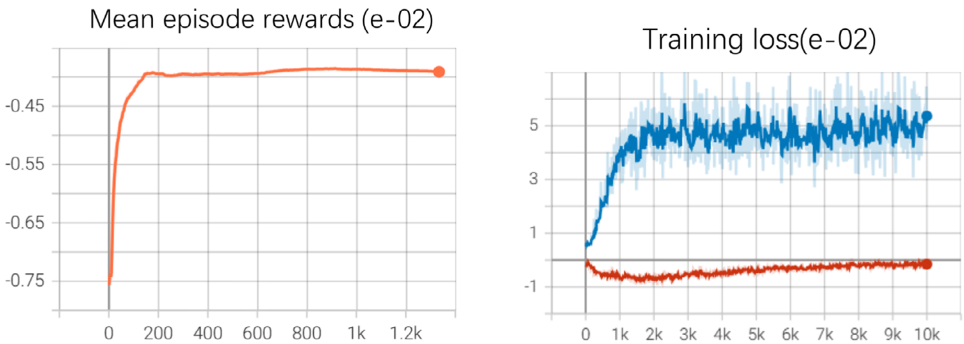
4.3 | Training Results of Printing Process Parameter Strategy Model

Based on the training results of the printing quality prediction model in Section 4.2, use the trained quality model as the environment. This section adopts reinforcement learning method, which trains the printing process parameter strategy model DDPG according to the description in Section 3.3, and



(a) $offset_x$ and $offset_y$ (b) $error_x$ and $error_y$

FIGURE 8 | The testing effect of PQPM.

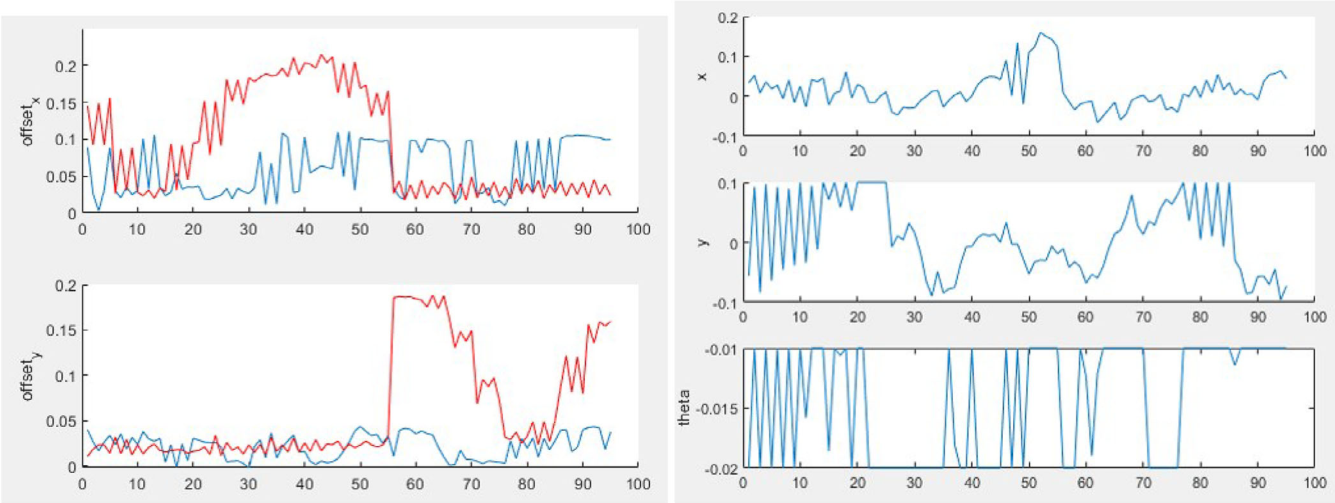


(a) The rewards of PPPSM (b) The loss of PPPSM

FIGURE 9 | The rewards and loss of training effect for PPPSM.

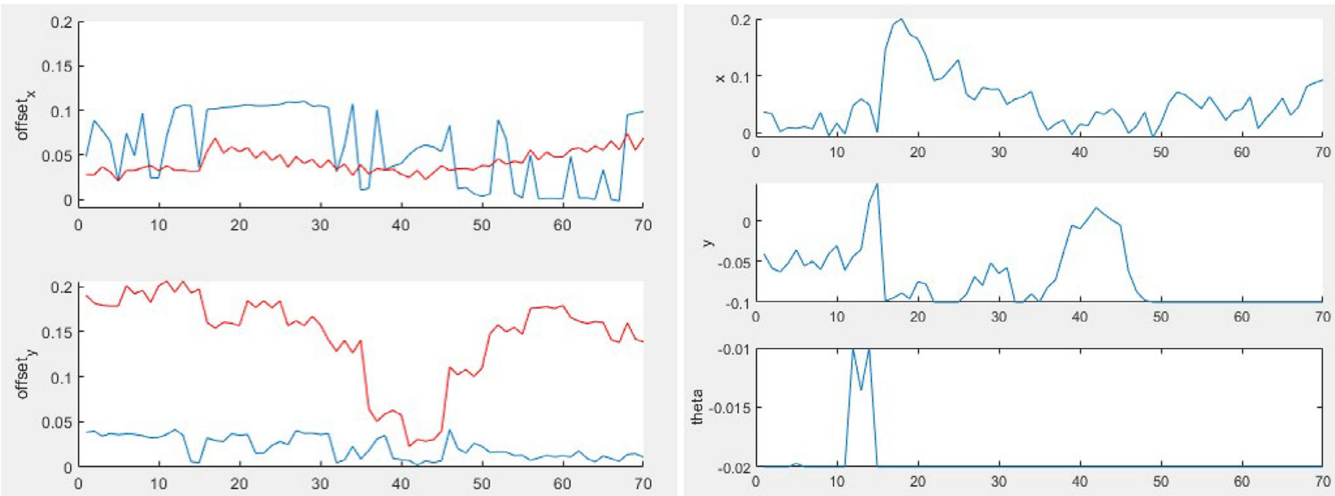
observes and analyzes the model test results. Figure 9a,b, respectively, show the reward curve and loss curve of the training process of the printing process parameter strategy model. The convergence effect of the printing process parameter strategy model during training can be seen from Figure 9.

Figure 10 shows the regulatory effect of the printing process parameter strategy model described in this paper on the SPI data in the 5.31-Match-SPI-STA-1.xlsx dataset in Table 1. The red curve in Figure 10 represents the x direction offset and y direction offset in the actual SPI data on the SMT production line, while the blue curve represents the correction result of the key process parameters generated by the strategy model acting on the real SPI data. The effectiveness of the printing process parameter strategy model can be seen from Figure 10a. Figure 10b shows the process parameters $\{offset_x, offset_x, offset_\Theta\}$ output by the printing process parameter strategy model. Consider using 0.1 as the upper limit of the qualification rate threshold, and the unqualified rate of x direction deviation in the original SPI data is $error_x = 0.3684$, the unqualified rate after correction is $error_x = 0.2105$. The unqualified rate of y direction deviation in the original SPI data is $error_y = 0.2316$, the unqualified rate after correction is $error_y = 0$. Figure 11 shows the regulatory effect of the printing process parameter strategy model described in this article on the SPI data in the 5.31-Match SPI-STA-2.xlsx dataset in Table 1. The effectiveness of the printing process parameter strategy model can also be seen from Figure 11a. Figure 11b shows the process parameters $\{offset_x, offset_x, offset_\Theta\}$ output by the printing process parameter strategy model. Similarly, considering 0.1 as the upper limit of the qualified rate threshold, the unqualified rate of x direction deviation in the original SPI data is $error_x = 0$, the unqualified rate after correction is $error_x = 0.3$. The unqualified rate of y direction deviation in the original SPI data is $error_y = 0.8671$, the unqualified rate after correction is $error_y = 0$. It is worth noting that the original x direction deviation in Figure 11a is qualified. After using the strategy model to correct the deviation, the unqualified rate of the original x direction deviation increases to 0.3, and the unqualified rate of the original y direction deviation decreases significantly from 0.8671 to 0. This indicates that the printing process parameter strategy model described in Section 3.3 and this section is not universal. At least in Figure 11, a significant correction in the y direction is achieved at the cost of partial failure rates in the x direction, which overall reflects the effectiveness of the policy model.



(a) $offset_x$ and $offset_y$ (b) The key process parameters $\{x, y, \theta\}$

FIGURE 10 | Comparison between true values and predicted values of $offset_x$ and $offset_y$ based on the key process parameters $\{x, y, \theta\}$ generated by PPPSM in 5.31-Match-SPI-STA-1.xlsx.



(a) $offset_x$ and $offset_y$ (b) The key process parameters $\{x, y, \theta\}$

FIGURE 11 | Comparison between true values and predicted values of $offset_x$ and $offset_y$ based on the key process parameters $\{x, y, \theta\}$ generated by PPPSM in 5.31-Match-SPI-STA-2.xlsx.

5 | Conclusion

The traditional SMT production line is equipped with experienced operators who interrupt the production process and adjust key process parameters based on production failure rate alarms. However, the development of artificial intelligence technology makes the adjustment of process parameters not entirely dependent on human operators. This paper uses a human in the environment fusion scheme to optimize the adjustment of key process parameters in the SMT production line, in order to improve the qualification rate and solve the problem of low production efficiency caused by pure manual adjustment of parameters. The paper uses deep reinforcement learning methods and multi-layer perceptrons to establish a printing process parameter strategy model and a printing quality prediction model, respectively, to achieve SPI and real-time adjustment of process parameters on the SMT production line, forming a complete closed-loop system for SPI correction. The experimental results indicate that the human on environment optimization scheme proposed in this paper has indeed improved the production qualification rate and made the SMT production line more intelligent. And experienced operators have the decision-making power to intervene at any time in the closed-loop system.

Author Contributions

Qianqian Zhang: writing – original draft, methodology, formal analysis, conceptualization. **Pengfei Li:** writing – original preparation, formal analysis, conceptualization. **Yun-Bo Zhao:** writing – review & editing,

supervision, formal analysis. **Yu Kang:** writing – review & editing, project administration, supervision.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Research data are not shared.

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