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Operation Parameters Optimisation of a Machine Swarm Using Artificial Intelligence

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***Abstract*—Due to improper setting of operating parameters, cigarette machines are subject to a high unqualified production rate. For this reason, in this study, a multiobjective optimisation (MOP) method based on the metaheuristic intelligence optimisation is proposed in this study. First, to eliminate interference parameters, the random forest (RF) is used to analyse the parameter importance of the cigarette machine and select the most important operation parameters for the multiobjective optimisation. Second, an artificial neural network (ANN) optimised by the grey wolf optimiser is designed to establish a mirror model of the cigarette machine to fast calculate the machine output quality factors, including the rod break rate, single cigarette weight, and circumference index. Lastly, an improved multiobjective grey wolf optimisation algorithm is used to optimise these three quality factors simultaneously to obtain the optimal operating parameters of the cigarette machine. A machine swarm (including four cigarette machines) in the real world is used to evaluate the developed optimisation method, and the testing results demonstrate that the proposed multiobjective optimisation method is able to improve the three quality factors by at least 50 %, which greatly reduces the unqualified rate of cigarettes.**

***Index Terms*—Multiobjective optimisation; Machine swarm; Production quality control; Artificial intelligence.**

I. INTRODUCTION

Despite the huge effort that has been made to encompass the concept of multiobjective optimisation (MOP) on production machines [1]–[4], the real-world application of this optimiser over a cigarette machine swarm has not yet been clarified. Currently, the standardised parameter and monitoring system for the cigarette machines is being implemented using the digital midline technology, which will be used to control the quality of the cigarette production [5]. A set of machine maintenance strategies will be established to reduce common equipment failures and maintain product quality stability. However, optimising a group of machine operation parameters is not yet considered in the current monitoring system. If the machine operation parameters are not in the best setting, the initial production quality will be at a low level, and consequently, the monitoring system will not perform its desired function. Hence, it is critical to find the optimal machine operation parameters for high-performance control of the production quality; however, the MOP for a single cigarette machine has not been found in open literature; no more to say the optimisation of a machine swarm. Motivated by this, this study attempts to solve the MOP for a cigarette machine swarm in engineering practice.

The first step in a MOP problem is to identify the input features of the model [6]. This is because in a real-world machine there are more than 60 operation parameters in a cigarette machine, while not all of them are informative. Generally, one should select the most presentative ones from all operation parameters. There are many feature selection algorithms in the open literature; for example, K-means [7], principal component analysis [8], singular value decomposition [9], Pearson correlation [10], mutual information [11], trees [12], and many others. Among these existing popular feature selection methods, random forest (RF) [13] is very suitable for real-time implementation because of the fast computation time and simple parameter setting. More importantly, RF can directly quantify the degree of importance of the original features, making the feature selection much more transparent and understandable. As a result, it is reasonable to use the RF for the selection of cigarette machine parameters.

A simplified model of the system of interest is essential for the multiobjective optimiser. This is because during optimisation searching, it always requests the computation cost as minimum as possible. In each iteration of the optimisation search, the optimiser needs to recall the system model. If the model is too complex, then the computation for calculating the search fitness result will be extremely huge. To simplify the mathematical model of the system, many order reduction methods [14] have been proposed; besides, the surrogate modelling technique with Gaussian processing [15] has been widely applied. However, most existing model reduction methods either scarify the model accuracy (e.g., order reduction methods) or increase the model computation cost. Recently, artificial neural network (ANN) surrogate modelling demonstrates promising potential in system model simplification [16]–[19]. Once the ANN surrogate model has been well trained, it will remain super high accuracy of the model outputs with very few computation efforts. However, during the ANN training process, the optimal ANN parameters are usually difficult to obtain. Metaheuristic

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intelligence optimisation, e.g., the grey wolf (GW) optimiser [20], can participate in the ANN training to search for the optimal ANN parameters. The original GW cannot well handle the trade-off between the local/global searching and population diversity. The latest research suggests that a suitable search strategy may enhance the balance of this issue. For example, improved grey wolf (IGW) with a new dimension learning-based hunting (DLH) search strategy [21]. However, to our knowledge, the selection of RF, the IGW-optimised ANN surrogate model, and the MOP based on IGW have not been adequately integrated for cigarette machines [22]–[27]. It is worth investigating the parameter optimisation of a cigarette machine swarm using these mentioned techniques [28]–[30], especially for using hybrid intelligent techniques [31]–[34].

This study aims to optimise the operation parameters of a cigarette machine swarm by appropriately integrating the RF selection, IGW-optimised ANN surrogate model, and IGW-based multiobjective optimiser. The RF is used to select the most informative parameters of cigarette machines to train a surrogate recurrent neural network (RNN) model of the cigarette machine. The RNN outputs are the three quality factors (i.e., the rod break rate, the single cigarette weight, and the circumference index). The IGW is adopted to optimise the parameters of the RNN model using a buckle of training data sets acquired from field tests. Then, the well-trained RNN model is used for the MOP of the machine swarm parameters to achieve a good balance between the three quality factors using the IGW optimiser. The results of the field tests demonstrate the effectiveness of the MOP method developed. The present method has already been used in real-world practice.

The organisation of this study is as follows. Section II describes the MOP procedure of the proposed method and Section III illustrates the field test results. Section IV draws the conclusions of this study.

II. PROPOSED METHOD

A. *Importance of Each Parameter*

Figure 1 shows an overview of the proposed method for optimising operation parameters of a machine swarm.

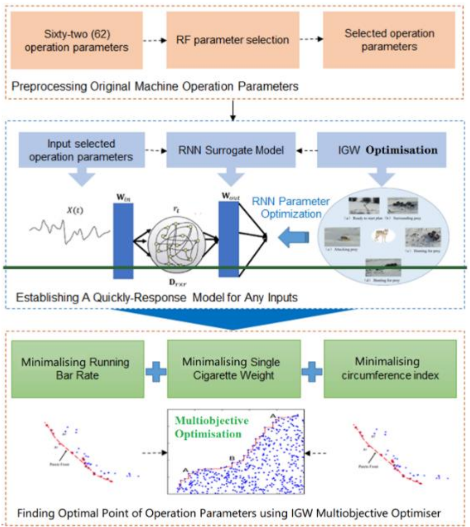


Fig. 1. Overview of the proposed method for optimisation of operation parameters.

In a single cigarette machine, there are 62 operation parameters, as listed in Table I. To remove useless parameters, the RF is used to evaluate the importance of each parameter and select the most informative parameters. Then, the selected parameters are used as the input of the RNN surrogate model of the cigarette machine. Historical data sets from real-world machines are used to train the RNN to establish a map connecting the input parameters and the three output quality factors (i.e., the rod break rate, the single cigarette weight, and the circumference index). The IGW is adopted to optimise the RNN model parameters during the training process. Then, the well-trained RNN model helps the IGW optimiser in the MOP process by providing super-fast responses to any trials of inputs during the IGW searching. A set of optimal operation parameters is obtained after the IGW optimisation to achieve a good balance between the three quality factors.

B. *RF Selection*

In Fig. 1, RF is a method that combines random node optimisation and bagging and uses a decision tree process to construct a forest of unrelated trees. For more details on RF refer to the work in [22]. The RF workflow is described below.

1. Define the training number N and the feature number M.
2. Define the selected feature number m (<<M).
3. Use bootstrap sampling to build the training sets.
4. Randomly select m features from M features in each node to calculate the best splitting method.
5. Grow each tree without pruning.

TABLE I. OPERATION PARAMETERS OF A SINGLE CIGARETTE MACHINE.

No.	Parameter	No.	Parameter
1	VE needle roller start-up correction	32	VE weight control system
2	VE setpoint bulking chute light barriers	33	VE suc. tape adj. upper warning limit
3	VE stop after bulking chute empty	34	VE suc. tape adj. lower warning limit
4	VE stop after bulking chute choke-up	35	VE suc. tape adj thread. pos. front
5	VE fluid. bed trough tob. thick. control	36	VE suc. tape adj thread. pos. rear
6	VE fluid. bed trough pressure start val.	37	VE weight deviation scale
7	VE fluid. bed trough pressure end value	38	VE/SE tobacco rod length
8	VE admixed air flap start val.递contr.	39	VE end-densing drive offset front
9	VE admixed air flap end value uncontr.	40	VE end-densing drive offset rear
10	VE air-jet fan speed	41	SE rod circumference setpoint
11	VE steep-angle conveyor prop. factor	42	Diameter/circumference display
12	VE interface type bulking chute photosensor	43	ODM no. of meas. cyc. to stop
13	VE motor type needle roller drive	44	ODM min. circumf. warning limit
14	VE suction air control	45	ODM max. circumf. warning limit
15	VE suct. rod conv. vac. pressure	46	ODM min. circumf. stop limit
16	VE suct. rod conv. vacuum pres. control KP	47	ODM max. circumf. stop limit

No.	Parameter	No.	Parameter
17	VE suct. rod conv. vacuum pres. control Tn	48	SE seam gluing acceleration offset
18	VE suct. air fan speed uncontrolled production	49	SE seam gluing initial glue feed
19	VE suction air fan speed at standstill	50	SE seam glue quantity corr. factor
20	VE densed end geometry	51	SE minimum seam glue quantity
21	VE trimmer height front	52	SE automatic glue supply system fitted
22	VE trimmer height rear	53	SE seam sealer start-up temperature
23	VE trimmer plate height front	54	SE seam sealer production temperature
24	VE trimmer plate height rear	55	SE garniture tape overspeed
25	VE menthol spraying fitted	56	SE garniture temperature
26	VE tobacco rod weight	57	SE seal. ch. height adj. calib. pos. front
27	VE suc. tape adj. start offset front	58	SE seal. ch. height adj. calib. pos. rear
28	VE suc. tape adj. start offset rear	59	SE diameter control system
29	VE suc. tape adj. prod. pos. front	60	SE front seal. chamber adj. start offset
30	VE suc. tape adj. prod. position rear	61	SE rear seal. chamber adj. start offset
31	VE IXM	62	SE sealing chamber version rear

When using RF to judge the operation parameters, a cost function must be provided. In this study, there are three factors available; to avoid conflict between different factors, this study uses the single cigarette weight (SW) as a cost function because this factor is the most widely used one in the industry. The cost function is then expressed as

$$f\left(SW\right) \leq 0.02\ g. \tag{1}$$

Equation (1) means that each cigarette weight must be less than 0.02 g.

The training data sets were collected using 100,000 cigarette production under the condition of factory setting of machine parameters. The number of random forests was set to 500. The RF assessment results are shown in Fig. 2. Figure 2 provides the first 21 most important parameters of the machine among the 62 parameters. As can be seen from the figure, each parameter has a certain influence on the performance of the quality of the cigarettes, among which the parameter no. 1 (i.e., the VE needle roller start-up correction in Table I) is of the highest importance, which is 4.43. In addition, the importance of parameter no. 10, parameter no. 18, parameter no. 7, and parameter no. 21 in Table I is more than 1.0, which are 3.11, 1.98, 1.86, and 1.20, respectively. The results indicate that these five parameters with the highest importance values could significantly affect machine production quality. The effects of parameter nos. 22, 23, 24, 53, 54, 60, 61, 48, 35, 33, 34, 36, 56, 15, 27, and 28 on the performance of the machine are gradually weakened. The remaining 41 parameters in Table I do not have an obvious effect on the performance of the machine production process.

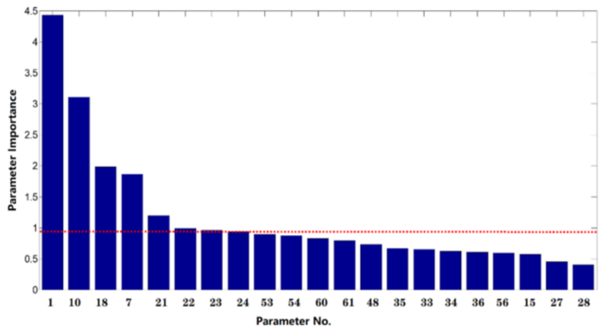


Fig. 2. Importance of machine operation parameters

Furthermore, the influence of these five main operation parameters (no. 1, no. 10, no. 18, no. 7, and no. 21) on the performance of the machine production ability is investigated in depth. In the test, the other 57 parameters are kept as factory setting values, and only these five parameters change their setting values in the production process. The results are shown in Figs. 3–7.

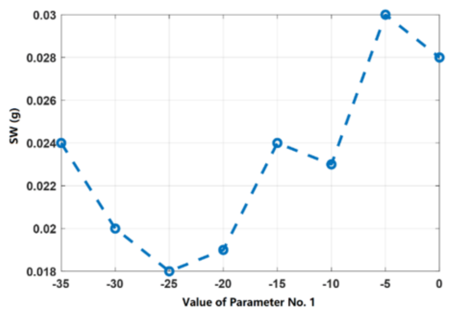


Fig. 3. Influence of operation parameter no. 1.

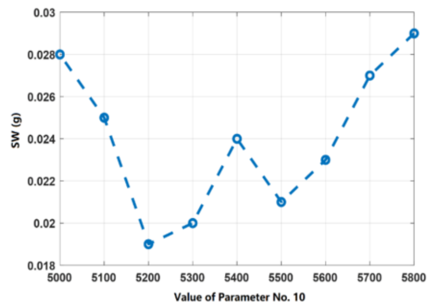


Fig. 4. Influence of operation parameter no. 10.

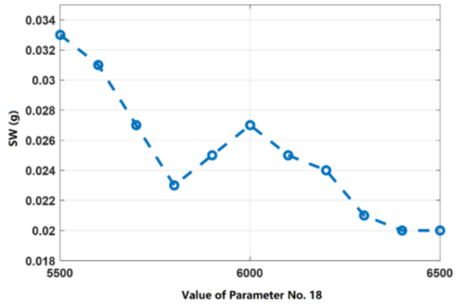


Fig. 5. Influence of operation parameter no. 18.

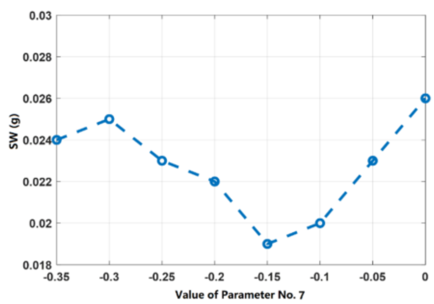


Fig. 6. Influence of operation parameter no. 7.

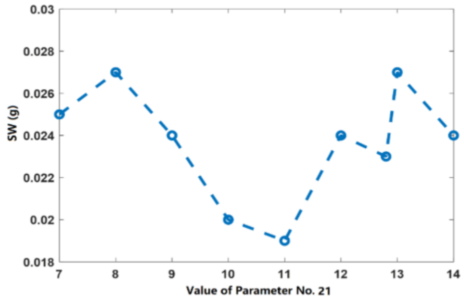


Fig. 7. Influence of operation parameter no. 21.

Figure 3 shows the performance of the machine production recorded by changing the operation parameter no. 1. The factory setting value of the parameter no. 1 is -10. At this moment, the corresponding production quality factor SW is 0.023 g, which indicates a small gap from the required target value of 0.02 g. By continuous correction of the parameter no. 1, it is found that when the value is between -25 and -20, the SW requirement can be met.

Figure 4 shows the performance of the machine production recorded by changing the operation parameter no. 10. The factory setting value of the parameter no. 1 is 5,600. At this moment, the corresponding production quality factor SW is 0.023 g, which indicates a small gap from the required target value of 0.02 g. By continuous correction of the parameter no. 10, it is found that when the value is between 5,200 and 5,300, the SW requirement can be met.

Figure 5 shows the performance of the machine production recorded by changing the operation parameter no. 18. The factory setting value of the parameter no. 1 is 5,800. At this moment, the corresponding production quality factor SW is 0.023 g, which indicates a small gap from the required target value of 0.02 g. By continuous correction of the parameter no. 1, it is found that when the value is between 6,400 and 6,500, the SW requirement can be met.

Figure 6 shows the performance of the machine production recorded by changing the operation parameter no. 7. The factory setting value of the parameter no. 1 is -0.25. At this moment, the corresponding production quality factor SW is 0.023 g, which indicates a small gap from the required target value of 0.02 g. By continuous correction of the parameter no. 1, it is found that when the value is between -0.15 and -0.1, the SW requirement can be met.

Figure 7 shows the performance of the machine production recorded by changing the operation parameter no. 21. The factory setting value of parameter no. 1 is 12.8. At this moment, the corresponding production quality factor SW is 0.023 g, which indicates a small gap from the required target value of 0.02 g. By continuous correction of the parameter no. 1, it is found that when the value is between 10 and 11, the SW requirement can be met.

From these observations, in Figs. 3–7, it can be seen that the quality of production is influenced by multiple parameters. It must perform MOP to set the optimal values of the machine operation parameters to guarantee production quality.

C. *RNN Surrogate Model*

As mentioned before, to reduce the computation cost of the MOP, one need to establish a surrogate model of the machine to fast respond to any input, which avoids extremely heavy computations during the MOP process due to recalling the complicated machine mathematical model.

This study adopts the RNN to establish the surrogate model. RNN is a new type of feedforward ANN, which means that the model parameters and computation complexity are within a considerable range. The detailed theory of RNN can be found in [23]. The input of the RNN are the five selected operation parameters (no. 1, no. 10, no. 18, no. 7, and no. 21), and the outputs are the three quality factors (i.e., the rod break rate, the single cigarette weight, and the circumference index). For the RNN model, the hidden layer number sets 8; the active functions use the ReLU function; the Softmax function is adopted in the output layer. The IGW is used to find the appropriate input layer weight coefficients W, hidden layer weight coefficients U, and output layer weight coefficients V.

To effectively train the RNN model, 100,000 training data sets collected in different combinations of the operation parameters of the cigarette machine were used in this study. Training data sets were completed using four cigarette machines in 6 months. The maximum optimisation iteration was 500. After the IGW-based training, the RNN model produced a training error of 0.001, which indicates good training accuracy. Then, 1,000 test data sets were used to evaluate the RNN model. Figure 8 shows the testing results.

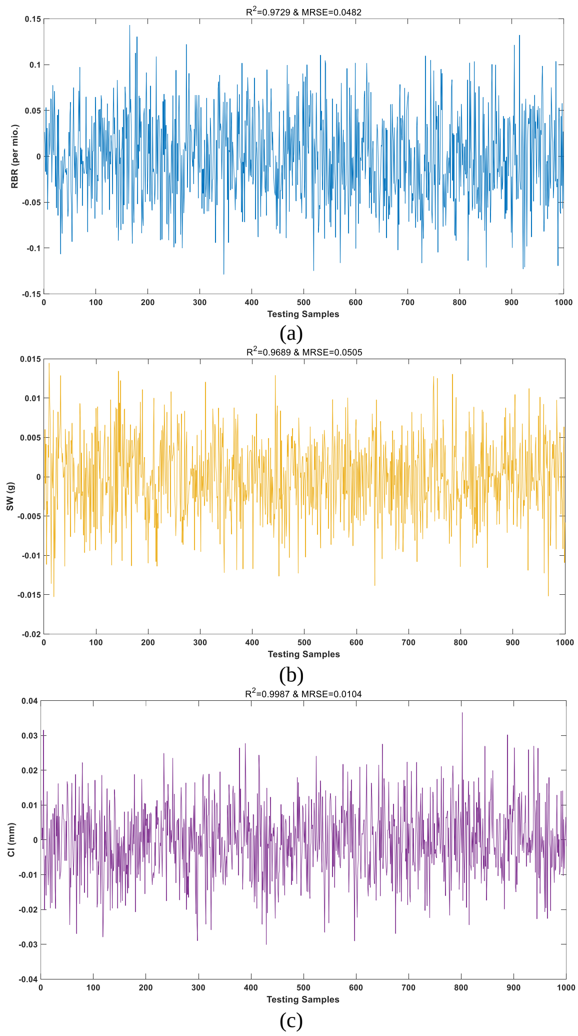


Fig. 8. Performance of the RNN model testing: (a) Accuracy of RNN prediction on the factor of rod break rate (RBR); (b) Accuracy of RNN prediction on the factor of single cigarette weight (SW); (c) Accuracy of RNN prediction on the factor of circumference index (CI).

As can be seen that, in Fig. 8(a), the predicted output rod break rate (RBR) of the RNN model is very accurate because the mean root square error (MRSE) between the ground truth and the RNN prediction is as small as 0.0482 and the R square (R2) of them is 0.9729. In Fig. 8(b), the MRSE and R2 of the second RNN output single cigarette weight (SW) are respectively 0.0505 and 0.9689. In Fig. 8(c), these two merits are 0.0104 and 0.9987. These observations indicate high performance of the RNN model.

D. *IGW-Based Multiobjective Optimisation*

After obtaining a well-trained RNN model, the MOP can be implemented. The IGW method is adopted as an optimiser to find a set of suitable values of the five input parameters to meet the following constraints:

$$f\left(RBR\right) \leq 1.4\ g, \tag{2}$$

$$f\left(SW\right) \leq 0.02\ g, \tag{3}$$

$$f\left(CI\right) \leq 0.055\ g. \tag{4}$$

To narrow the IGW search range, based on the RF selection results in Section II-A, the search ranges for inputs are defined in Table II. Table III lists the search results. As can be seen in Table III, the IGW continuously searches for the suitable combination of the five operation parameters to generate the required production quality indexes. With increasing optimisation iterations, the RBR and CI gradually decrease, while the SW maintains at an acceptable level. After 160 iterations, the final optimal values of the input parameters are -25.3, 5,210, 6,396, -0.15, and 10.2, respectively.

TABLE II. SEARCH CONSTRAINS FOR THE FIVE INPUT PARAMETERS.

Input	Lower limit	Upper limit
Parameter no. 1	-30	-20
Parameter no. 10	5100	5400
Parameter no. 18	6300	6500
Parameter no. 7	-0.16	-0.9
Parameter no. 21	9	12

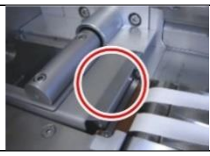
TABLE III. IGW-BASED MULTIOBJECTIVE OPTIMISATION.

Iteration	Input	Value	Fitness
1	Parameter no. 1	-27.5	f(RBR) = 1.43 g f(SW) = 0.018 g f(CI) = 0.053 g
	Parameter no. 10	5,230	
	Parameter no. 18	6,450	
	Parameter no. 7	-0.13	
	Parameter no. 21	11.1	
Iteration	**Input**	**Value**	**Fitness**
40	Parameter no. 1	-24.7	f(RBR) = 1.08 g f(SW) = 0.016 g f(CI) = 0.051 g
	Parameter no. 10	5,268	
	Parameter no. 18	6,500	
	Parameter no. 7	-0.13	
	Parameter no. 21	11.0	
Iteration	**Input**	**Value**	**Fitness**
80	Parameter no. 1	-23.5	f(RBR) = 0.88 g f(SW) = 0.016 g f(CI) = 0.048 g
	Parameter no. 10	5,177	
	Parameter no. 18	6,500	
	Parameter no. 7	-0.14	
	Parameter no. 21	10.6	
Iteration	**Input**	**Value**	**Fitness**
120	Parameter no. 1	-25.1	f(RBR) = 0.72 g f(SW) = 0.017 g f(CI) = 0.046 g
	Parameter no. 10	5,205	
	Parameter no. 18	6,326	
Iteration	**Input**	**Value**	**Fitness**
	Parameter no. 7	-0.13	
	Parameter no. 21	10.3	
Iteration	**Input**	**Value**	**Fitness**
160	Parameter no. 1	-25.3	f(RBR) = 0.34 g f(SW) = 0.016 g f(CI) = 0.041 g
	Parameter no. 10	5,210	
	Parameter no. 18	6,396	
	Parameter no. 7	-0.15	
	Parameter no. 21	10.2	

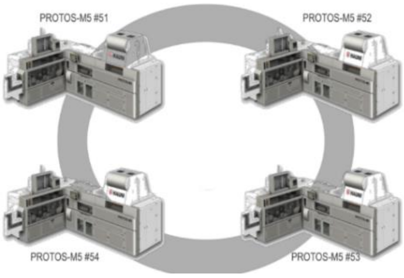
III. FIELD TEST WITH A MACHINE SWARM

A group of four machines was used to verify the validity of the optimal values of the input parameters in the field test. To set the five parameters of each machine as the optimal values, Table IV lists a set of machine settings before the field test.

TABLE IV. MACHINE RESETS BEFORE THE FIELD TEST.

Location	Action	Factory setting	Correction
	Needle setting	0 turns	3 turns
	Suction Rod Conveyor distance to VE mainframe (left)	140.18 mm	140 mm
	Suction Rod Conveyor distance to VE mainframe (right)	206.6 mm	207 mm
	Suction Rod Conveyor height (left)	68.6 mm	68.9 mm
	Suction Rod Conveyor height (right)	25.2 mm	25.4 mm
	Trimmer Disc Rear height to paddle wheel (Rear Trimmer)	0.4 mm	0.5 mm
	Trimmer Disc Rear height to paddle wheel (Front Trimmer)	0.35 mm	0.5 mm
	Trimmer height to Trimmer Rail	0.7 mm	0.3 mm

Then, the parameter resets were completed for the four machines, as shown in Fig. 9. In the field test, the machines produced 10,000 cigarettes using the optimal parameters and another 10,000 cigarettes using the factory setting. Table V compares the performance of machine production.



(a)

(b)

Fig. 9. Four machines in the field test: (a) The machine swarm used for the field testing; (b) An image of one machine in the field testing.

As can be seen in Table V, with optimised operation parameters, each machine is capable of producing high-quality cigarettes that meet the required standards of the three factors. The average quality index values obtained are RBR = 0.3825, SW = 0.0165, and CI = 0.039. However, without optimisation, the machines cannot produce qualified production due to the fact that RBR = 1.5775, SW = 0.036, and CI = 0.0785. Compared to the results obtained, the RBR index is improved by 75.75 % when using the proposed method, the SW index is improved by 54.17 %, and the CI index is improved by 50.32 %. To highlight the performance of the proposed method, Table VI lists the comparison results with the popular genetic algorithm (GA) and particle swarm optimisation (PSO) based optimisers.

TABLE V. FIELD TEST RESULTS.

	Input	Value	Machine #51	Machine #52	Machine #53	Machine #54	Machine Swarm
Factory setting	Parameter no. 1	-10	*f*(RBR) = 1.67 g *f*(SW) = 0.035 g *f*(CI) = 0.078 g	*f*(RBR) = 1.53 g *f*(SW) = 0.041 g *f*(CI) = 0.083 g	*f*(RBR) = 1.49 g *f*(SW) = 0.035 g *f*(CI) = 0.072 g	*f*(RBR) = 1.62 g *f*(SW) = 0.033 g *f*(CI) = 0.081 g	*f*(RBR) = 1.5775 g *f*(SW) = 0.036 g *f*(CI) = 0.0785 g
	Parameter no. 10	5,600					
	Parameter no. 18	5,800					
	Parameter no. 7	-0.25					
	Parameter no. 21	12.8					
IGW optimised setting	Parameter no. 1	-25.3	*f*(RBR) = 0.41 g *f*(SW) = 0.016 g *f*(CI) = 0.041 g	*f*(RBR) = 0.39 g *f*(SW) = 0.017 g *f*(CI) = 0.037 g	*f*(RBR) = 0.34 g *f*(SW) = 0.015 g *f*(CI) = 0.040 g	*f*(RBR) = 0.39 g *f*(SW) = 0.018 g *f*(CI) = 0.038 g	*f*(RBR) = 0.3825 g *f*(SW) = 0.0165 g *f*(CI) = 0.039 g
	Parameter no. 10	5,210					
	Parameter no. 18	6,396					
	Parameter no. 7	-0.15					
	Parameter no. 21	10.2					

TABLE VI. COMPARISON OF DIFFERENT METHODS.

Method	RBR	SW	CI
GA-based	73.26 % ↑	53.63 % ↑	48.13 % ↑
PSO-based	74.29 % ↑	53.52 % ↑	47.68 % ↑
Proposed method	75.75 % ↑	54.17 % ↑	50.32 % ↑

In Table VI, it can be seen that the performance improvement generated by the proposed method is better than that using the GA and PSO optimisers. As a result, the proposed method can solve the MOP problem of cigarette machines and is applicable and practicable for real-world applications.

IV. CONCLUSIONS

This paper aims to optimise the operation parameters of a cigarette machine swarm by appropriately integrating the RF selection, IGW-optimised ANN surrogate model, and IGW-based multiobjective optimiser. The numerical evaluation selected five most important parameters (parameters no. 1, no. 10, no. 18, no. 7, and no. 21 in Table I) of 62 machine operation parameters. Then the field test demonstrates that, compared to the factory setting, the RBR index is improved by 75.75 % using the proposed method, the SW index is improved by 54.17 %, and the CI index is improved by 50.32 %. The main conclusions are drawn as follows:

1. The RF selects the most useful machine parameters, which helps the RNN to establish a very accurate surrogate model. The RNN model is able to predict the quality factors very precisely;
2. The present RNN-IGW MOP method is capable of finding the optimal values of machine operation parameters, which significantly improves the production quality;
3. The RBR, SW, and CI indexed have been improved by at least 50 % using the proposed method;
4. The performance improvement of the proposed method for each index is better than that using the GA and PSO methods.

It can be seen from the field tests of the proposed method for the cigarette machine swarm that the manufacturing sector will significantly increase its production quality rate, which will definitely reduce production costs and efficiency. As a result, the proposed method can be applied to the manufacturing sector. The future plan will implement and evaluate the proposed method on more machines, as well as different types of machines.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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