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RESEARCH ARTICLE

An Intelligent Control Model Based on Digital Twin Technology and Optimized Least-Squares Support Vector Regression for Predicting Electromagnetic Brake Assembly Quality

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ABSTRACT Electromagnetic (EM) brakes are widely applied in many automation and control fields. Assembly quality defects in EM brakes can significantly reduce braking performance and pose potential safety risks. The primary challenge in assembly quality control is the ability to predict product quality and prevent potential failures. In view of the lack of quality information interaction and real-time feedback in the traditional quality prediction process, an intelligent predictive quality control model for the assembly process of EM brakes is proposed in this paper. First, we introduce an assembly quality control model based on digital twin (DT) technology. Second, a data-driven quality prediction algorithm is developed using least-squares support vector regression (LSSVR) and improved particle swarm optimisation (IPSO). To reduce the complexity of the prediction process, grey relational analysis (GRA) is used to analyse and extract key quality characteristics data. EM friction brakes are employed as an example to analyse the product assembly process, and the results provide valuable insights into the implementation of DT technology. Finally, the feasibility of the developed prediction model is verified with real assembly datasets. The results demonstrate the effectiveness and precision of the DT model and the GRA-IPSO-LSSVR method in predicting assembly quality.

INDEX TERMS Digital twin, particle swarm optimization, predictive control, quality control, reliability engineering, support vector machines.

I. INTRODUCTION

With the expansion of the electromagnetic (EM) brake industry and the intensification of global competition, enterprises urgently need to improve product quality to obtain a long-term competitive advantage in the market economy. The quality control of the assembly process is key to realise the highest level of product quality. However, unstable factors and fluctuations in the assembly process can lead to high-risk quality problems and result in the EM brakes failing to meet specifications. Currently, product quality control mainly relies on manual experience and general testing. This outdated quality management method has been unable to keep up with the trend of intelligent manufacturing. Therefore, it is vital to establish an intelligent control model for assembly quality prediction to enhance the quality of EM brakes.

Quality prediction technology forms the basis of quality control and intelligent decision making. In the assembly environment, accurate prediction of product quality indicators can enable businesses to spot potential issues early on and take proactive measures to maintain these indicators within acceptable limits. Assembly quality indicators can be

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continuous values, such as assembly accuracy [1], or discrete values, such as quality levels [2]. Typically, product quality prediction methods fall into one of two categories: physical methods [3] and data-driven methods [4]. Owing to the uncertain and nonlinear nature of the EM brake assembly process, physical methods have limited ability to describe complex assembly processes and cannot predict quality with sufficient accuracy and adaptability. In contrast, data-driven quality prediction methods are more practical and generalisable. They involve training prediction models and learning potential patterns from historical data [5].

Manufacturing enterprises need to analyse and process a large amount of process data before implementing quality prediction technology. Additionally, they should select quality prediction models that are stable and interpretable. Machine learning (ML) models such as decision trees, support vector machines, and artificial neural networks have gained popularity in the field of quality prediction. Schnell et al. [6] predicted the capacity of lithium-ion batteries based on ML models such as decision trees and random forests. This research method can further improve the quality of lithium-ion battery production processes. In industrial manufacturing, deep neural networks (NNs) commonly discard valuable information related to quality variables from the raw data. To address this issue, Wang et al. [7] introduced a novel layer-wise residual prediction network based on a stacked auto-encoder (LR-SAE), which reflects the deviation between actual values and quality variable predictions to guide the feature learning process at each layer. In multi-stage manufacturing processes, the variability in product dimensions is a critical factor, as undetected defects can easily propagate downstream. Peres et al. [8] discussed the application of various machine learning classifiers in real-world automotive multi-stage assembly lines to predict dimension defects. Stock et al. [9] employed data mining technology and neural network technology to predict the early quality of lithium-ion batteries (LIBs). The prediction results underscore the great potential of data-driven models for predicting LIB quality in production. To identify defective product outputs before production and assembly, Bak et al. [10] developed a quality prediction model based on shallow neural networks. The model was verified using the dataset of the aluminium die-casting process, and the prediction accuracy was 99.6%. Dealing with abundant and unbalanced data is a common scenario during the construction of quality prediction models. To address this challenge, Feng et al. [11] employed random forest to reduce dimensionality and analyse key quality features. Subsequently, the synthetic minority oversampling technique and Adaboost method was used to classify the assembly quality of imbalanced data for hub bearings. Zhou et al. [12] used a fine Gaussian support vector machine and the random forest method to predict product quality, and the prediction accuracy was verified using the Secom public dataset. From the above literature, it is evident that data-driven quality prediction approaches based on ML models have emerged as the most promising tools for quality modelling in manufacturing processes. However, because the assembly process of EM brakes is dynamic, the aforementioned quality prediction methods cannot predict and comprehensively control product quality in real time during the assembly process. Furthermore, for many complex electromechanical products, the level of intelligence and global optimisation in the assembly process remain insufficient. Therefore, further interconnection and integration of the information and physical aspects of product assembly are essential to adapt to current customised production models.

Since its inception, digital twin (DT) technology has rapidly developed, owing to the popularity of model-based system engineering, computer-aided design concepts, and industrial Internet of Things (IIoT) technology [13]. Research institutions have extensively studied fundamental concepts [14], [15], theoretical frameworks [16], [17], and key technologies [18], [19] related to DT. DT technology acts as a link between the physical and virtual worlds. It creates high-density, multi-dimensional digital models with powerful real-time capabilities to mimic real-world entities. Moreover, in both academia and industry, DT technology has been applied to product quality control, and it has transitioned from theoretical to practical applications. Zhao et al. [20] presented a modeling approach for Digital Twin Process Models (DTPM) in manufacturing process planning. This method discusses the acquisition and management of real-time and simulation data, as well as the integration of physical and virtual spatial data. Liu et al. [21] combined DT with fault prediction and maintenance. A three-tier super-network model was constructed, and warning features from the physical, virtual, and service layers were selected as input parameters for the fault prediction model. Real-time maintenance strategies were formulated using the simulation and optimization capabilities of the virtual model. Liu et al. [22] introduced a DT-driven traceability and dynamic control method for machining quality, enabling fault source traceability, prediction, and dynamic control of the machining quality of diesel engine connecting rods. Wei et al. [23] investigated a strategy for implementing physical entities in manufacturing system DTs. The implementation of the proposed strategy was demonstrated using an example of tool life prediction for a computer numerical control machine tool based on DT. Polini and Corrado [24] introduced the DT tool for product assembly manufacturing processes, considering geometric change information from part design to assembly. Through DT technology, a continuous flow of information exchange was established to bridge the gap between the digital and physical aspects of the entire product lifecycle management. Liu et al. [25] presented an architecture for real-time visual monitoring, operational state analysis, and quality prediction in complex die-casting smart manufacturing, utilizing DT and data-driven techniques. Pang et al. [26] developed an intelligent, data-driven product quality control model based on DT techniques and physical information system simulation methods.

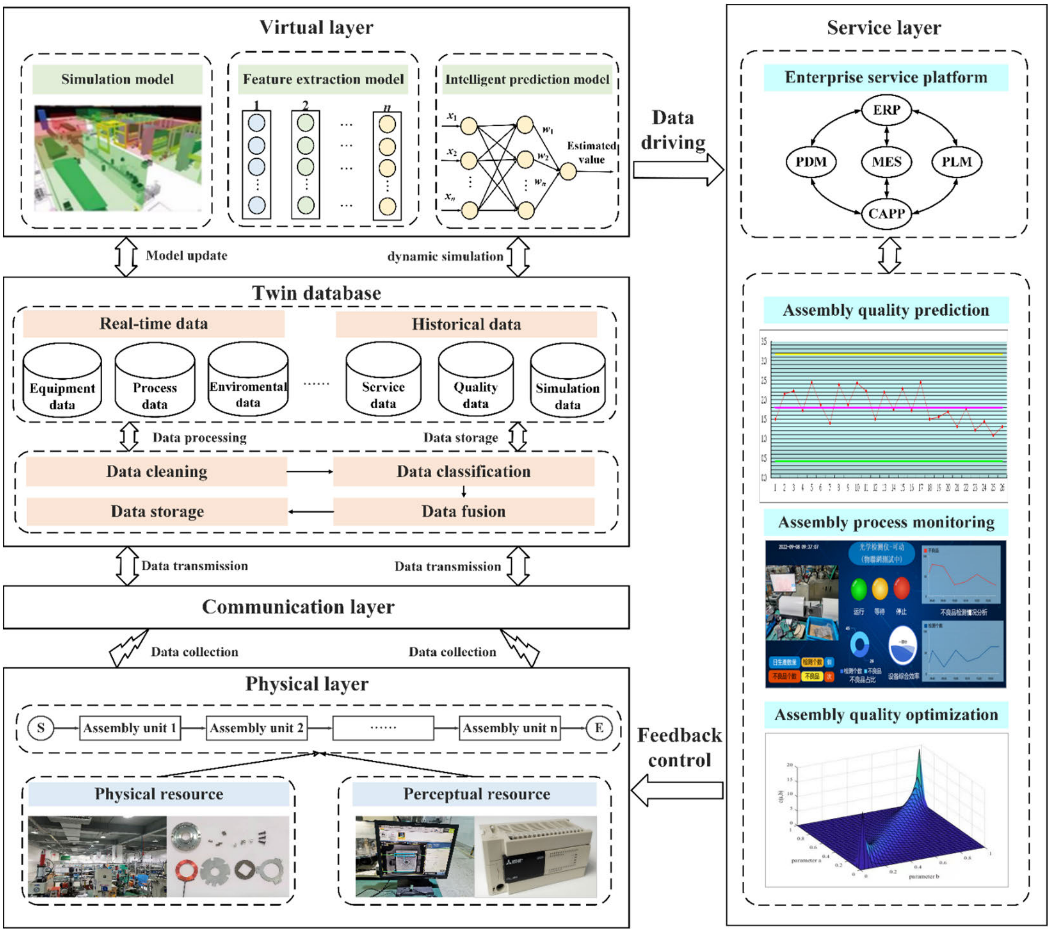

FIGURE 1. Framework of intelligent predictive control model of assembly quality based on DT technology.

The antecedent research attests to the capacity of DT technology in augmenting bidirectional interaction of quality data between virtual and physical assembly spaces. Furthermore, the integration of a data-driven quality control model manifests commendable efficacy in predicting product quality. However, these contribution overlooks the resolution of inherent complexities and interdependencies within the quality dataset. Consequently, building upon the foundation of the DT technology and data driven-based quality control model, GRA is employed to scrutinize the intricate relationships between assembly process data and quality characteristics. This analytical approach aims to provide dependable intput variables for precise quality predictions. Moreover, utilizing the LSSVR as the quality prediction model, this paper takes into consideration the stochastic nature and weight issues associated with particle initialization during the modeling process. To enhance the precision of quality predictions, the synthesis of good point set (GPS) and a dynamic weight formula is incorporated into the particle swarm optimisation (PSO) algorithm.

The paper is organized as follows in the subsequent sections. Section II introduces the DT technology-based quality predictive control model framework for the product assembly process. Section III presents a DT data-driven assembly quality prediction method. We develop integrated algorithms based on GRA, IPSO, and LSSVR for this prediction method. Section IV presents an example of the assembly process of EM brakes to illustrate the quality predictive control process based on DT technology and the GRA-IPSO-LSSVR method. Furthermore, the accuracy of the GRA-IPSO-LSSVR algorithm is verified using assembly process data from the EM brakes. Section V provides a comprehensive analysis of the quality prediction results, elucidating the superiority of the approach proposed in this paper. Section VI presents the conclusion of the study.

II. FRAMEWORK OF DT TECHNOLOGY-BASED INTELLIGENT PREDICTIVE CONTROL MODEL FOR ASSEMBLY QUALITY

DT technology is an essential pathway for traditional manufacturing to transition into intelligent manufacturing. With the widespread adoption of intelligent manufacturing, the intelligent predictive control model has become a vital tool for quality management in the product manufacturing process. This research seeks to harness he advantages of DT technology in creating an intelligent predictive control model for EM brake assembly.

First, during the assembly process, production data can be continuously monitored in real time and compared with the digital model, enabling quality control at every stage. Additionally, the virtual side allows for the automatic prediction of assembly quality through the collection of production data from the assembly process. These real-time decision results can be adjusted and verified by quality engineers, leading to a continuous improvement in production efficiency and product quality. Building upon the traditional model-based design (MBD) approach, this paper introduces an innovative model framework for intelligent predictive control of assembly quality (Fig. 1). The proposed model comprises a physical layer, virtual layer, twin database, communication layer, and service layer. The details are described in the following section.

A. THE PHYSICAL LAYER

The physical layer encompasses the physical and sensory resources involved in the product assembly process. Physical resources include products, personnel, equipment, materials, and environments. Sensory resources include sensors, programmable logic controller, and radio-frequency identifications. Each activity within the assembly process forms a unit of a physical assembly system, tightly interconnected through physical and sensory resources. The substantial volume of data collected during the physical assembly process serves as the basis for modelling the prediction of assembly quality and updating the virtual model.

B. THE VIRTUAL LAYER

The virtual layer provides a real-time, dynamic, omnidirectional, and accurate mapping of the physical assembly process. Because the virtual model is continuously updated, quality engineers can monitor and track the actual product assembly condition at any time. The proposed virtual layer encompasses three-dimensional simulation, quality feature extraction, and quality prediction models. Within the virtual layer, the quality state of the current assembly product is automatically predicted and diagnosed using real-time data in the database and ML algorithms, and the results are fed back to the service layer.

C. TWIN DATABASE

Twin data are the key elements driving the entire quality intelligent predictive control model. They are derived from the physical layer, virtual layer, and service layer, and are further categorised into historical data and real-time data. Historical data include test data, quality data, and simulation data, while real-time data include equipment parameters, environmental data, and assembly process data. The final fused data are used for diagnosing and predicting assembly process quality using various algorithms, including data conversion, classification, analysis, and fusion algorithms.

D. THE COMMUNICATION LAYER

The communication layer is vital for ensuring bidirectional, real-time communication and facilitating continuous iterative optimisation in the assembly process. Industrial communication protocols such as OPC-UA (object linking and embedding for process control unified architecture) and Modbus are used to collect heterogeneous data from the physical model. Technologies such as IIoT, 5G, and Bluetooth are used for data transmission. Two-way communication between the virtual layer and the service layer can be achieved through interfaces such as Socket, MQSeries, and other software applications, facilitating the delivery of assembly instructions, data transmission and reception, and message synchronisation. Conversely, the simulation and prediction data generated in the virtual layer can be stored in the twin database using interfaces such as java database connectivity, open database connectivity, and other database connections.

E. THE SERVICE LAYER

The service layer is composed of enterprise software, such as manufacturing execution system, computer-aided process planning, and enterprise resource planning. These software applications can perform various quality management functions, including assembly quality optimisation, assembly quality prediction, and assembly quality monitoring, utilising a substantial amount of twin data generated during the virtual-real interaction process. The applications provide real-time and reliable quality control services for the physical assembly shop through feedback control instructions.

III. DT DATA-DRIVEN ASSEMBLY QUALITY PREDICTION METHOD

To achieve quality predictive control of the EM brake assembly process, an integrated method for high-performance prediction needs to be developed. In this paper, a DT and data-driven GRA-IPSO-LSSVR prediction algorithm is proposed, and the algorithm development process is illustrated in Fig. 2.

The proposed method includes three parts. The first part involves the selection and analysis of key quality characteristic parameters during the assembly process. To be more specific, we preprocess the initial data and calculate the importance of characteristic parameters based on GRA. A grey correlation threshold of 0.7 is set, and quality data exceeding this threshold are chosen. The second part entails the establishment and training of the optimal LSSVR model. Additionally, we employ an IPSO algorithm for joint optimization of LSSVR's hyperparameters. In the third part, we conduct a performance analysis of the well-trained LSSVR model and apply it for product quality prediction.

A. GRA ALGORITHM FOR QUALITY PARAMETER SELECTION

GRA, a component of grey system theory, is used to investigate the correlation between various factors. In this paper, GRA is used to analyse the degree of influence of assembly quality data on specific quality characteristics. The core idea revolves around simplifying a complex system issue by reducing it to a one-dimensional problem. In essence, GRA performs quantitative analysis by converting multiple

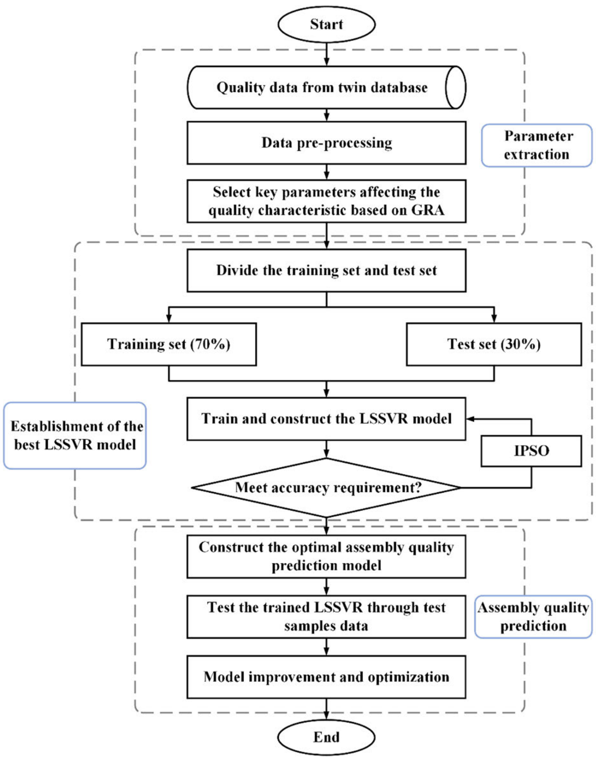

FIGURE 2. **Digital twin data-driven assembly quality prediction method.**

parameters into a single value using quantitative metrics [27]. Its calculation steps are as follows:

Step 1: The data sequence for the quality characteristic (reference sequence) is assumed as $X_0 = \{x_0(k), k = 1, 2, \ldots, n\}$, and the characteristic parameters (comparison sequence) is assumed as $X_i = \{x_i(k), k = 1, 2, \ldots, n\}, (i = 1, 2, \ldots, m)$, where m is the number of quality characteristic parameters, and n is the length of assembly quality characteristic variables.

Step 2: Directly calculating the degree of grey incidence may produce unreliable results because the quality characteristic parameters have different magnitudes. To conduct more precise quantitative analysis, it's necessary to transform experimental data into dimensionless data. Therefore, the quality data are first normalised. In this paper, the minimum-maximum normalisation method is used to scale the sample data between 0 and 1. The formula is as follows:

$$x_i(k) = \frac{x_i(k) - \min(X_i)}{\max(X_i) - \min(X_i)} \tag{1}$$

Step 3: The relative coefficient between each characteristic parameter and quality characteristic is calculated using the formula:

$$r(x_0(k), x_i(k)) = \frac{\min_i \max_k \Delta_i(k) + \rho \min_i \max_k \Delta_i(k)}{\Delta_i(k) + \rho \min_i \max_k \Delta_i(k)} \tag{2}$$

where $\Delta_i(k) = |x_0(k) - x_i(k)|$; the parameter ρ is the resolving coefficient which usually considered 0.5, $\rho \in [0, 1]$.

Step 4: The grey relational degree λ for each characteristic parameter is calculated:

$$\lambda = r(X_0, X_i) = \frac{1}{n}\sum_{k=1}^{n} r(x_0(k), x_i(k)) \tag{3}$$

The key characteristic parameters with strong correlation are compared and selected. The higher the λ, the more relevant the characteristic parameters are to the assembly quality characteristic in the experiment.

B. LSSVR ALGORITHM FOR ASSEMBLY QUALITY PREDICTION

Support vector regression (SVR) is a regression extension of the support vector machine that provides benefits like robust generalization and rapid convergence. SVR is particularly effective for applications involving small samples and nonlinear problems. Moreover, SVR has good robustness, generalisation and learning properties, owing to the introduction of a structured minimum criterion [28].

For a given assembly quality data training set, $T = (x_i, y_i), i = 1, \ldots, l \in (R^n \times \gamma)^l$, where $x_i \in R^n$ are the input characteristic parameters, and $y_i \in \gamma = R$ is the true assembly quality characteristic value. SVR takes assembly quality data and employs a nonlinear transformation to map it into a high-dimensional space. Within this high-dimensional feature space, it then converts the nonlinear model into a linear regression model. The assembly quality prediction function is constructed as follows:

$$F(x) = \omega^T \varphi(x) + b \tag{4}$$

where $F(x)$ is the assembly quality prediction function, $\varphi(x)$ represents a non-linear mapping that takes input variables and transforms them into a high-dimensional feature space. The function is defined by two parameters: ω, which is the weight vector, and b, which is the threshold value.

According to the structural risk minimisation principle, the objective function and constraints of the SVR model are based on the ε-insensitive loss function, as follows:

$$\min \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*) \tag{5}$$

$$s.t. \begin{cases} y_i - \omega^T \cdot \varphi(x_i) - b \leq \varepsilon + \xi_i \\ \omega^T \cdot \varphi(x_i) + b - y_i \leq \varepsilon + \xi_i^* \quad (i = 1, 2, \cdots, n) \\ \xi_i \geq 0, \xi_i^* \geq 0 \end{cases} \tag{6}$$

where C is the penalty factor, ξ_i and ξ_i^* are relaxation factors, and ε is the insensitivity factor.

In the objective, the first part $1/2\,\|\omega\|^2$ reflects the complexity of the model, while the second part $C\sum_{i=1}^{l}(\xi_i + \xi_i^*)$ corresponds to the training error. Therefore, the regularisation parameter C is an important user-defined model parameter for SVR, and it determines the cost of the trade-off between model complexity and prediction accuracy. Therefore, its

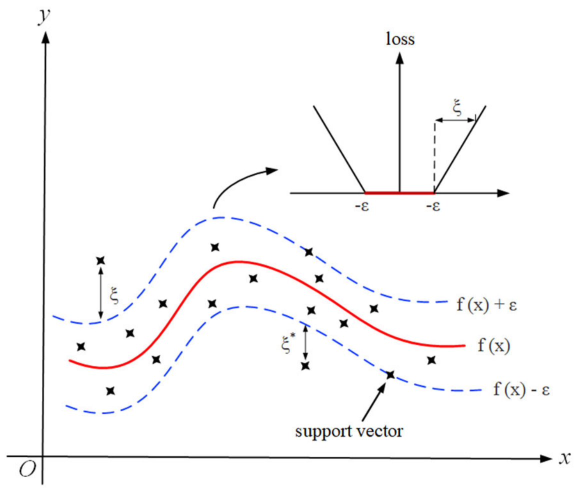

FIGURE 3. Schematic of the SVR principle.

value should be carefully specified to ensure prediction performance. The schematic of the SVR principle is shown in Fig. 3.

To reduce computational complexity, LSSVR is introduced through the method of converting the original inequality constraints into equality constraints. These equations are typically determined using mathematical tools such as Lagrange multipliers to meet the requirements of optimization problems [29]. The square loss function e_i^2 is introduced to replace the insensitive ε loss function. The problem is transformed into the following equation:

$$\min J(\omega, C, e) = \frac{1}{2}\|\omega\|^2 + \frac{C}{2}\sum_{i=1}^{l} e_i^2 \tag{7}$$

$$s.t.\ y_i - (\omega^T \cdot \varphi(x_i) + b) = e_i, \quad i = 1, 2, \cdots l \tag{8}$$

To simplify the calculation, the Lagrange function [30] is introduced to solve the problem:

$$\begin{aligned} L(\omega, b, e, \alpha, \beta) &= J(\omega, C, e) \\ &\quad - \sum_{i=1}^{l} \alpha_i \left(\omega^T \varphi(x_i) + b + e_i - y_i\right) \end{aligned} \tag{9}$$

where α_i is the Lagrange multiplier vector, $\alpha_i = [\alpha_1, \alpha_2, \ldots, \alpha_l]$.

According to the Karush-Kuhn-Tucker conditions, the partial derivative of the function $L(\omega, b, e, \alpha)$ with respect to the optimisation objective is set to 0:

$$\begin{cases} \dfrac{\partial L}{\partial \omega} = 0 \rightarrow \omega = \sum_{i=1}^{l} \alpha_i \varphi(x_i) \\ \dfrac{\partial L}{\partial b} = 0 \rightarrow \sum_{i=1}^{l} \alpha_i = 0 \\ \dfrac{\partial L}{\partial e_i} = 0 \rightarrow \alpha_i = Ce_i \\ \dfrac{\partial L}{\partial \alpha_i} = 0 \rightarrow \omega^T \varphi(x_i) + b + e_i - y_i = 0 \end{cases} . \tag{10}$$

The kernel function $K(x_i, x)$ is chosen instead of $\varphi(x_i)\cdot\varphi(x)$, and these equations can be converted into the following form:

$$\begin{bmatrix} 0 & 1 & \cdots & 1 \\ 1 & K(x_i, x) + 1/C & \cdots & K(x_i, x) \\ \vdots & \vdots & \ddots & \vdots \\ 1 & K(x_i, x) & \cdots & K(x_i, x) + 1/C \end{bmatrix} \begin{bmatrix} b \\ \alpha_1 \\ \vdots \\ \alpha_l \end{bmatrix} = \begin{bmatrix} 0 \\ y_1 \\ \vdots \\ y_l \end{bmatrix} \tag{11}$$

The assembly quality characteristic prediction function is further solved as follows:

$$F(x) = \sum_{i=1}^{l} \alpha_i K(x_i, x) + b \tag{12}$$

Typically employed kernel functions such as linear, polynomial, and Gaussian kernels are available. In this paper, we opt for radial basis kernel functions $K(x_i, x)$ for our analysis.

$$K(x, x_i) = \exp\left(-\frac{\|x - x_i\|^2}{2\gamma^2}\right) \tag{13}$$

where x_i is the key characteristic parameter input variables calculated using GRA, and γ is the radial base width, $\gamma > 0$.

$$F(x) = \sum_{i=1}^{l} \alpha_i \exp\left(-\frac{\|x - x_i\|^2}{2\gamma^2}\right) + b \tag{14}$$

C. IPSO ALGORITHM FOR LSSVR PARAMETERS OPTIMISATION

Typically, the initial values of the regularisation parameter C and the kernel parameter γ of LSSVR are determined empirically, which does not guarantee a globally optimal solution. To enhance the prediction accuracy of assembly quality characteristic values, the IPSO algorithm proposed in this study is employed to find the globally optimal solution for (C, γ).

The PSO algorithm is a swarm intelligence evolutionary algorithm jointly proposed by Kennedy and Eberhart in 1995 [31]. The computational steps of PSO are straightforward and can be described in five stages: initialisation, fitness calculation, determination of termination conditions, updating velocity and position, and updating the guide. The velocity and position update equations are as follows:

$$\begin{aligned} V_i(t+1) &= wV_i(t) + c_1 r_1 [pbest_i - X_i(t)] \\ &\quad + c_2 r_2 [gbest_i - X_i(t)] \end{aligned} \tag{15}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{16}$$

where $X_i(t) = (x_{i,1}, x_{i,2}, \ldots, x_{i,n})$ and $V_i(t) = (v_{i,1}, v_{i,2}, \ldots, v_{i,n})$ represent the position and velocity of the ith particle in an n-dimensional space. We have w as the inertia weight, c_1 and c_2 as the learning factors or acceleration coefficients, and r_1 and r_2 as random numbers following a uniform distribution $U(0,1)$. $pbest_i$ and $gbest_i$ denote the individual optimal position and population optimal position explored by the ith particle, respectively.

The PSO algorithm employs a random approach to generate the initial population, which cannot guarantee the diversity of the initial population and the effective extraction of useful information from the search space [32]. To tackle the issue of uneven population initialisation, this paper incorporates the theory of GPS to redesign the initialised population space. The basic definition and construction of a GPS are as follows:

Step 1: Let G_s be a unit cube in s-dimensional Euclidean space; if $z = (z_1, z_2, \ldots, z_s) \in G_s$, define the set containing n elements as

$$P_n(k) = \left\{(\left\{z_1^{(n)} * k\right\}, \left\{z_2^{(n)} * k\right\}, \cdots, \left\{z_s^{(n)} * k\right\}), 1 \le k \le n\right\} \tag{17}$$

Step 2: Take $z = 2cos(2\pi k/p), 1 \le k \le s$, where p satisfies the least prime of $(p-3)/2 \ge s$ or $\left\{e^k, 1 \le k \le s\right\}$.

Step 3: If the deviation $\phi(n)$ of $P_n(k)$ satisfies the following equation:

$$\phi(n) = C(z, \tau)n^{-1+\tau} \tag{18}$$

where $C(z, \tau)$ is a constant related only to z, and τ is an arbitrary positive number, then $P_n(k)$ is said to be a GPS, and z is a good point.

To assess the effectiveness of the GPS method, the overall population distributions generated using this theory and the random method are compared in Fig. 4 and Fig. 5. The initial number of solutions is set to 30, with each individual's dimension set to 2. Furthermore, the regularisation parameter C and kernel parameter γ of LSSVR are allowed to vary in the range [0, 10]. Each point in the Figure represents a feasible solution (C, γ). The Fig. 4 shows that the randomly generated two-dimensional point set exhibits local concentration and lacks regularity. In contrast, the solution set generated by the GPS theory is more uniformly distributed throughout the search space. This uniform distribution of feasible solutions enhances the optimisation process.

The inertia weights w serve as fundamental control parameters for algorithm development and exploration capabilities, significantly influencing the optimisation performance of the PSO algorithm. For PSO algorithms prone to premature convergence, stagnation, or local extrema, nonlinear dynamic inertia weight coefficients can be employed. The inertia weights increase as the particles converge on objective values or when the region is locally optimal. Conversely, the inertia weights decrease when the objective values of the particles are more dispersed. Moreover, smaller inertia weights are assigned to particles with objective function values smaller than the average objective value, retaining them for further exploration. In this research, smaller particle fitness values represent a better solution. In contrast, larger inertia weights are assigned to particles with less than optimal objective function values, bringing them closer to the search region of the globally optimal particle [33]. The nonlinear dynamic

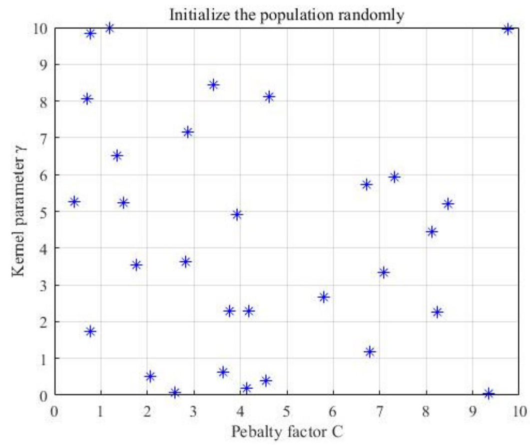

FIGURE 4. Initialisation of population based on a random method.

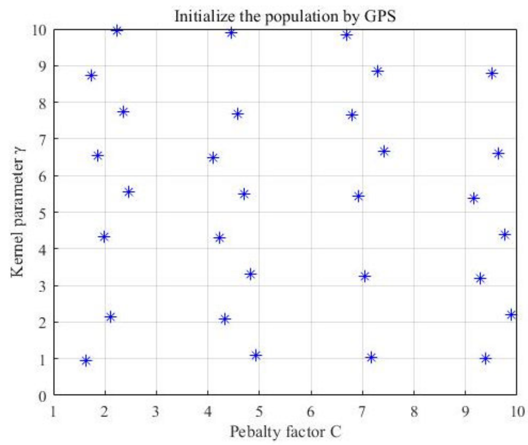

FIGURE 5. Initialisation of population based on the GPS method.

inertia weighting function is as follows:

$$w = \begin{cases} w_{\min} - \dfrac{(w_{\max} - w_{\min}) * (F - F_{\min})}{F_{avg} - F_{\min}} & F \le F_{avg} \\ w_{\max} & F \ge F_{avg} \end{cases} \tag{19}$$

where w_{min} and w_{max} denote the minimum and maximum values of w, respectively; F denotes the current fitness value of the particle; and F_{avg} and F_{min} denote the current average and minimum target values of all particles, respectively.

The proposed IPSO algorithm for parameter selection of the LSSVR model is shown in Fig. 6. The main steps are as follows:

Step 1: Initialise algorithm parameters, including population size, number of iterations, and acceleration factor.

Step 2: Set the position of the initial solution (C, γ) using the GPS theory.

Step 3: Assess the fitness of the population particles by calculating the root-mean-square error (RMSE) between the predicted and experimental values of mass characteristics during the LSSVR model's training process, using the

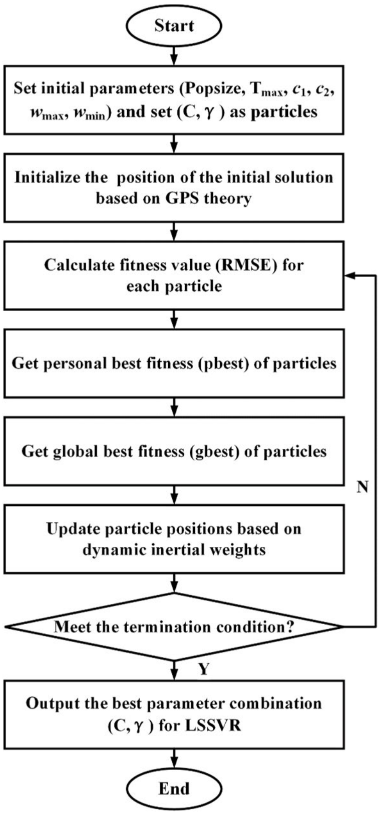

FIGURE 6. The flow chart of the proposed IPSO algorithm.

following formula:

$$RMSE = \sqrt{\frac{1}{l}\sum_{i=1}^{l}\left(F\left(x_i\right) - y_i\right)^2} \tag{20}$$

where y_i is the actual assembly quality characteristic value, $F(x_i)$ is the estimated value, and l is the total number of samples.

Step 4: Compare particle fitness values, and select individual facilitators and global leaders.

Step 5: Adopt the nonlinear dynamic inertia weight coefficient of Formula (19), and update the position and velocity of the particle according to Formulas (15) and (16).

Step 6: Determine whether the termination condition is met. If yes, output global optimal solutions C and γ. Otherwise, go to Step 3.

IV. CASE STUDY

The quality of EM brakes plays a critical role in the proper functioning of mechanical equipment. However, owing to the lack of strict quality control in the assembly process of EM brakes, the likelihood of failure can easily increase. Therefore, this paper uses a disc EM brake developed by a company in Zhejiang, China as an example, applying DT technology and the GRA-IPSO-LSSVR method for quality predictive control in the assembly process. These EM brakes are primarily utilised for arm control in robotic applications, as depicted in the structural diagram shown in Fig. 7.

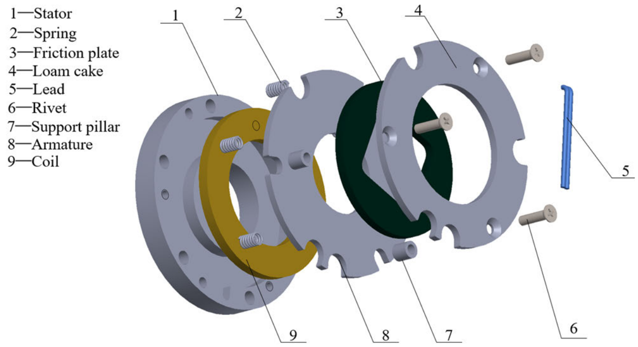

FIGURE 7. Schematic of the disc EM brake structure.

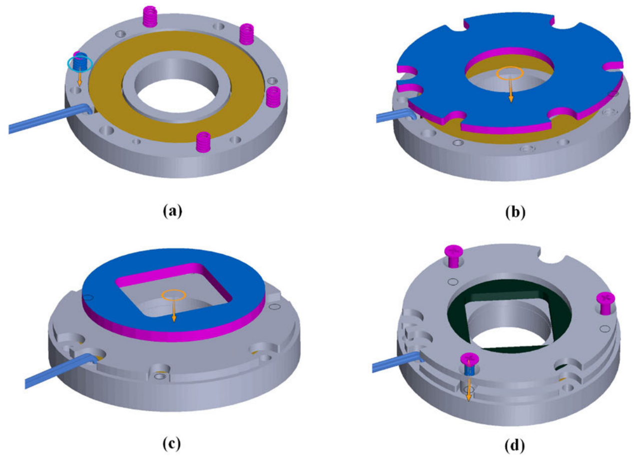

FIGURE 8. Part of the assembly process of the disc EM brakes. (a) Install the spring into the spring hole. (b) Install the armature on the spring. (c) Install the friction plate on the armature. (d) Tighten the screw to secure the brake.

A. ASSEMBLY PROCESS ANALYSIS OF DISC EM BRAKES

The production of disc EM brakes involves a series of manufacturing and assembly processes, from customer requirements to final products. The entire assembly production line comprises assembly machines, quality characteristic monitoring equipment, and worker operation stations. The assembly process of the disc EM brakes encompasses various steps, including part cleaning and inspection, wire winding without bones, wire package processing, electrical testing, assembly of parts, potting, vacuum drying, and quality testing. Part of the assembly process is depicted in Fig. 8.

Each assembly process has a significant impact on the final quality of the EM brakes, necessitating strict monitoring and control during assembly. During the installation of the spring, verifying its correct position and pre-pressure range is crucial. Regarding the armature, checks should be made for proper positioning and running-in state, and machining accuracy must conform to the required standards. During installation, the gap between the friction disc and the armature and the wear state and surface quality of the friction disc should also be examined. Additionally, during screw tightening, the tightening torque and sequence should be given close attention. Manufacturing companies must pay close attention to

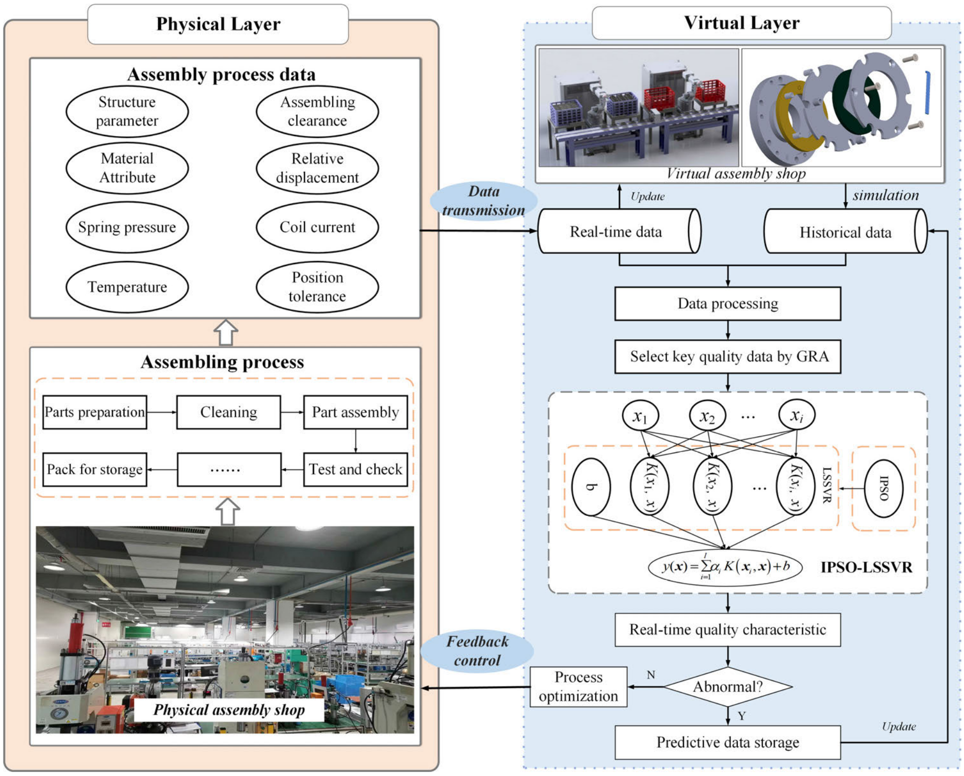

FIGURE 9. Part of the assembly process of the disc EM brakes.

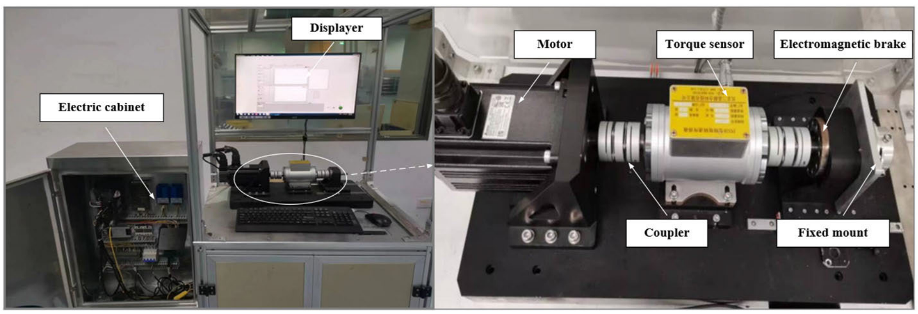

FIGURE 10. Static braking torque test platform on assembly line.

the testing process and methods to ensure potential problems are not overlooked. Therefore, it is crucial for manufacturing companies to anticipate and address quality issues in advance during the complex assembly process of EM brakes.

B. IMPLEMENTATION PROCESS OF DT TECHNOLOGY AND GRA-IPSO-LSSVR METHOD

Because EM brakes are critical for safety and reliability during operation, special attention must be devoted to quality management during assembly. This paper applies quality predictive control technology driven by DT and the GRA-IPSO-LSSVR method to the assembly process of disc EM brakes. The proposed implementation flow is illustrated in Fig. 9. Advanced data acquisition equipment and multidisciplinary coupling simulation methods are employed to achieve precise mapping from the physical layer to the virtual layer. Simultaneously, through intelligent quality prediction technology, quality diagnosis and prediction are conducted in the virtual layer, followed by optimisation of the physical assembly process. Starting from the input of materials and information in the assembly process to the output of the final product quality, an ideal closed-loop control is established.

Real-time data from the assembly process—including spring pressure, relative displacement of parts, assembly clearance, structural parameters captured by sensors, and data recorded by operators during assembly (such as coil current and torque magnitude)—are dynamically collected

TABLE 1. Detailed description of assembly process quality data.

Parameters	Quality characteristics	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5
X_1	Friction plate square hole diameter (mm)	35.013	35.062	35.039	25.243	25.020
X_2	Inside diameter of upper cover (mm)	47.080	47.025	47.114	37.045	37.060
X_3	Resistance value (Ω)	29.300	29.000	28.900	36.020	36.200
X_4	Clearance between the armature and the stator (mm)	0.119	0.151	0.166	0.291	0.281
X_5	Flatness of armature (mm)	0.012	0.021	0.015	0.014	0.018
X_6	Brake thickness (mm)	17.909	19.053	17.983	16.070	15.803
X_7	Clearance from the loam cake to the friction plate (mm)	8.544	8.490	8.530	5.529	5.489
X_8	The flatness of the loam cake (mm)	0.030	0.017	0.017	0.022	0.028
X_9	Clearance between the loam cake and armature (mm)	2.611	3.080	2.604	2.755	3.417
X_{10}	Concentricity of the friction plate (mm)	0.019	0.022	0.037	0.030	0.039
X_{11}	Spring installation height (mm)	6.576	6.568	6.574	6.569	6.565
X_{12}	Torque of the lock screw (N·m)	4.556	9.602	4.996	2.822	3.277
T	Static friction braking torque (N·m)	9.559	11.200	8.642	3.289	3.310

TABLE 2. Relational coefficient between each parameter and static braking torque.

No.	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}
1	0.5014	0.4055	0.5643	0.7309	0.7287	0.7544	0.9627	0.7291	0.7870	0.7288	0.8963	0.8371
2	0.5176	0.4167	0.5900	0.6988	0.6963	0.7656	0.9050	0.6964	0.7596	0.6963	0.8473	0.9420
3	0.4923	0.3995	0.5581	0.7516	0.7483	0.7330	0.9966	0.7484	0.8096	0.7488	0.9260	0.8760
4	0.5082	0.3800	0.7893	0.5614	0.5587	0.9696	0.6576	0.5588	0.5917	0.5589	0.6517	0.9060
5	0.5384	0.4313	0.4388	0.8958	0.8872	0.6672	0.9203	0.8875	0.9805	0.8877	0.8871	0.9830
6	0.4910	0.3961	0.5566	0.7522	0.7492	0.7110	0.9966	0.7493	0.8329	0.7493	0.9266	0.8649
7	0.5420	0.4312	0.4381	0.8892	0.8844	0.6752	0.9235	0.8848	0.9717	0.8844	0.8910	0.9850
8	0.4993	0.4048	0.5754	0.7379	0.7320	0.7272	0.9669	0.7321	0.8035	0.7326	0.9013	0.8590
9	0.5408	0.4293	0.4389	0.8937	0.8859	0.6741	0.9208	0.8858	0.9766	0.8861	0.8901	0.9702
10	0.4987	0.4036	0.5467	0.7392	0.7344	0.7430	0.9723	0.7342	0.7977	0.7343	0.9040	0.8568
11	0.4706	0.3847	0.5289	0.8101	0.8060	0.6642	0.9756	0.8060	0.8847	0.8064	0.9879	0.9355
12	0.5946	0.4611	0.4736	0.7765	0.7724	0.7511	0.9272	0.7725	0.8585	0.7729	0.9620	0.8619
13	0.4981	0.3992	0.5652	0.7394	0.7340	0.7245	0.9687	0.7343	0.7951	0.7348	0.9041	0.8373
14	0.5254	0.3893	0.8233	0.5419	0.5394	0.9138	0.6303	0.5396	0.5807	0.5396	0.6254	0.8203
15	0.5380	0.4293	0.6077	0.6683	0.6634	0.8423	0.8510	0.6636	0.7173	0.6637	0.7987	0.8844

through the IIoT. These data are processed and used to update the active DT model. Conversely, the GRA algorithm is employed to extract assembly quality data in the virtual layer and select parameter variables with a high degree of correlation with the prediction target. Subsequently, the key quality parameters serve as inputs for the IPSO-LSSVR prediction model, with the output being the predicted value of the quality characteristic. This automated online quality prediction process allows for the swift determination of whether the quality of the EM brakes meets the standards. If the criteria are met, the predicted data are stored as historical data in the twin database. Additionally, a substantial amount of data generated through simulation in the virtual layer can be used to train the model, further enhancing prediction accuracy. If the criteria are not met, the relevant quality data are transmitted to the quality department. Quality engineers analyse the results and devise improvement plans, which may involve adjustments to equipment parameters, process flow, and assembly sequence, to ensure product quality and reduce manufacturing costs.

C. ASSEMBLY QUALITY PREDICTION EXPERIMENT FOR EM BRAKES

1) DATA SET DESCRIPTION

Static braking torque is one of the most critical mass characteristics of an EM brake. Insufficient braking torque results in poor braking performance, while excessive braking torque may cause brake failure or damage. Therefore, the manufacturer must monitor and ensure that the braking torque is within the range required by the customer. The EM brakes assembly line contains many quality characteristic tests. For this case study, 78 sets of historical data were obtained through devices such as coordinate projectors and specialized torque test platforms. Each sample was labeled from 1 to 78 according to its acquisition time. After analysis and expert selection, 12 quality characteristic parameters are used as primitive variables for GRA-IPSO-LSSVR, and static braking torque is used as quality prediction target. The static braking torque test bench of the experimental samples is shown in Fig. 10, and Table 1 provides the specific characteristic parameters of some experimental samples.

2) KEY QUALITY CHARACTERISTIC PARAMETERS EXTRACTION

In this paper, the GRA method is employed to identify variables that significantly influence static braking torque. The identified variables are used as reliable input variables for LSSVR model training. Specifically, 12 quality characteristic parameters (X_1 to X_{12}) are used as comparison sequences, while static braking torque (T) is treated as the reference sequence.

First, the experimental dataset is standardised according to Formula (1). Using Formula (2), the correlation coefficient between each characteristic parameter and static braking torque is calculated, with the resolution coefficient "ρ" set to 0.5. The correlation coefficient quantifies the level of correlation between two random variables. Some of the computed results are displayed in Table 2.

Since the correlation coefficient provides a measure of correlation between the comparison sequence and the reference sequence at each time point, yielding multiple values, it's essential to consolidate these coefficients at each time moment into a single value. Consequently, the grey relational degree of each characteristic parameters of assembly process is calculated using Formula (3). The computed results are presented in Table 3 and are sorted for comparison as follows:

$$X_{12} > X_7 > X_{11} > X_9 > X_6 > X_4 > X_{10} > X_8 > X_5 > X_3 > X_1 > X_2$$

The input variables for the quality prediction model are selected according to the values of each grey relational degree. As indicated in Table 3, the torque of the lock screw (X_{12}) exhibits the strongest correlation, with a calculated value of 0.8938. Additionally, the coefficients of the correlations between the clearance from the loam cake to the friction plate (X_7) and the spring installation height (X_{11}) exceed 0.85. This suggests that variations in these variables will significantly impact braking torque. The grey relational degrees of $X_9, X_6, X_4, X_{10}, X_8$, and X_5 are between 0.7 and 0.8. Typically, variables with grey relational degrees exceeding 0.7 are considered key influencing factors. Therefore, the abovementioned nine parameters are selected as inputs for the braking torque prediction model.

TABLE 3. Grey relational degree of quality characteristic parameters.

Number	Grey relational degree	Number	Grey relational degree
X_1	0.5078	X_7	0.8816
X_2	0.4021	X_8	0.7261
X_3	0.5811	X_9	0.7935
X_4	0.7300	X_{10}	0.7262
X_5	0.7260	X_{11}	0.8611
X_6	0.7549	X_{12}	0.8938

TABLE 4. IPSO parameter settings.

Parameters	Explanation	Value
Popsize	Population size	30
T_{max}	Maximum number of iterations	60
c_1	Accelerated factor	2
c_2	Accelerated factor	2
w_{max}	Maximum inertia weight	1
w_{min}	Minimum inertia weight	0.4
C	Penalty factor	[0, 10]
γ	Kernel parameter	[0, 10]

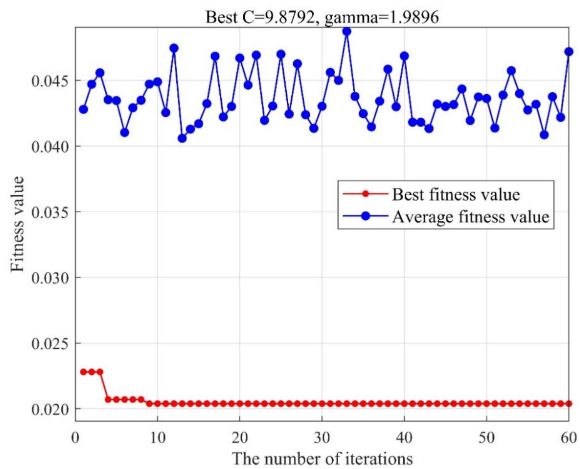

FIGURE 11. IPSO algorithm iteration process.

3) ESTABLISHMENT OF OPTIMAL LSSVR MODEL

The current study employs the IPSO algorithm to automatically determine the optimal combination of parameters (C, γ) for the LSSVR model and applies it to predict static braking torque. To finetune the (C, γ) parameters of the LSSVR model, the parameters of the IPSO algorithm are continuously adjusted to achieve maximum optimisation. The preset parameters of the particle swarm algorithm used in the experiments are outlined in Table 4, with all other parameters retained as default. The best fitness value and the average fitness value change curves for 60 iterations are recorded in Fig. 11.

According to Fig. 11, when the iterations tend to be stable, the optimal penalty factor C is computed as 9.8792, and the optimal kernel parameter γ is determined as 1.9896. The fitness value is calculated as 0.0204. These optimal parameters (C, γ) are utilised to train the LSSVR model using input variables X_4 - X_{12}, with the output variable defined as the static friction torque T. Consequently, the proposed model is considered an optimal prediction model for static friction torque.

V. RESULT AND DISCUSSION

A. PREDICTION RESULT

In this study, the first 70% of the total samples are designated as the training set, while the remaining 30% are set as the test set. The 23 test sets are input into the constructed LSSVR prediction model to assess the model's accuracy and generalisation ability. The estimated results and errors are depicted in Fig. 12.

To further validate the superiority of the proposed prediction model, static frictional braking torque is predicted using the same dataset through the PSO-LSSVR and GRA-PSO-LSSVR methods. Fig. 13 displays the prediction error outcomes obtained from various models. Additionally, an objective comparison of the predictive performance of these three models is conducted using the correlation coefficient (R^2), mean absolute error (MAE), and mean absolute percentage error (MAPE). Generally, a higher R^2 value (closer to 1) indicates better approximation performance, while lower MSE and MAPE values suggest closer alignment with actual values. The relevant expression is as follows:

$$R^2 = 1 - \frac{\sum_{k=1}^{N} (T_{actual} - T_{estimated})^2}{\sum_{k=1}^{N} (T_{actual} - T_{mean})^2} \tag{21}$$

$$\mathrm{MAE} = \frac{1}{N} \sum_{k=1}^{N} |(T_{actual} - T_{estimated})| \tag{22}$$

$$\mathrm{MAPE} = \frac{1}{N} \sum_{k=1}^{N} \left| \frac{T_{actual} - T_{estimated}}{T_{actual}} \right| \tag{23}$$

where T_{mean} is the average value of the static barking torque. The parameter N is the number of samples and is taken as 23.

Table 5 presents the results obtained from the three models. The R^2 value of GRA-IPSO-LSSVR is 0.9718. This indicates that the proposed method exhibits the best prediction performance among the three models. The MAE and MAPE values of the model are 0.3132 and 2.94%, respectively, indicating that the proposed method has the smallest error. The results of GRA-PSO-LSSVR and PSO-LSSVR show that the predictive performance of the model improved across all three evaluation metrics after parameter selection using the GRA approach. Specifically, the R^2 value increased from 0.8533 to 0.9506. Furthermore, when comparing the predictive results of GRA-PSO-LSSVR and the proposed model, it is evident that the utilization of GPS and dynamic inertia weighting led to a significant reduction in MAPE from 4.50% to 2.94%. These results demonstrate that the IPSO algorithm can effectively select the optimal combination of LSSVR parameters, thereby improving prediction accuracy. Additionally, the use of GRA can efficiently identify key quality characteristic parameters, reducing the complexity of model calculations.

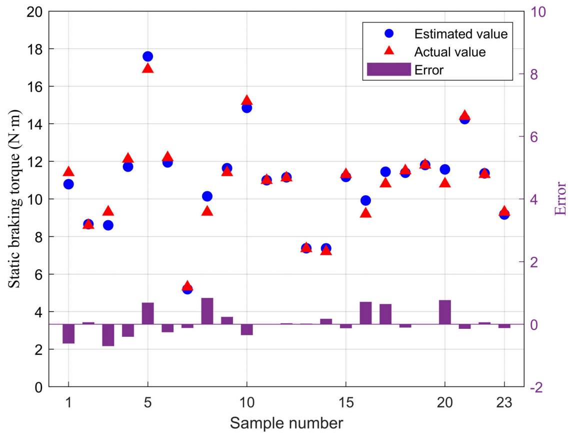

FIGURE 12. Predictions and error obtained using the GRA-IPSO-LSSVR method. (Error = $T_{estimated} - T_{actual}$, where $T_{estimated}$ and T_{actual} are the estimated value and the actual value of static braking torque, respectively.)

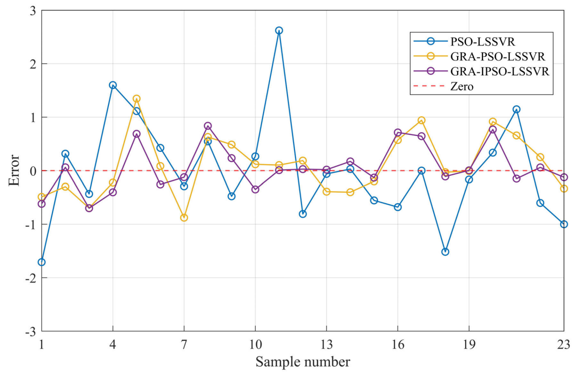

FIGURE 13. Comparison of prediction errors based on PSO-LSSVR, GRA-PSO-LSSVR, and GRA-IPSO-LSSVR models.

TABLE 5. Evaluation indicators for different prediction models.

Prediction model	R^2	MAE	MAPE
PSO-LSSVR	0.8533	0.7261	0.0654
GRA-PSO-LSSVR	0.9506	0.4455	0.0450
GRA-IPSO-LSSVR	0.9718	0.3132	0.0294

B. DISCUSSION

In line with the current trend of intelligent manufacturing, DT technology and quality data are employed for the predictive control of assembly quality. The proposed framework for DT-driven intelligent predictive control in assembly quality is designed to empower stakeholders with the ability to make well-informed decisions based on a variety of quality objectives. By employing a closed-loop DT approach, manufacturers of EM brakes can harness the full potential of twin quality data throughout the assembly process, and predict trends in static braking torque based on the trained GRA-IPSO-LSSVR intelligent algorithm.

Drawing upon the results of the experiments conducted, several key conclusions can be inferred. Firstly, it is evident that the prediction outcomes improve following the selection of relevant quality characteristics. This suggests that there may be redundant quality characteristics in the assembly process that have less relevance to the final product quality. The calculation procedure of GRA not only quantifies the relationship between parameters and static braking torque but also contributes to enhancing prediction accuracy. Consequently, the selection of critical quality characteristic parameters plays a pivotal role in predicting assembly quality issues. Secondly, the IPSO demonstrates advantages over traditional PSO, indicating that the performance of the algorithm is influenced by the particle swarm initialization method and weight update strategy. The adoption of the GPS and dynamic inertia weight strategies appears to address these aspects effectively. As such, this paper posits that the quality predictive control model based on DT and GRA-IPSO-LSSVR can be extended to a broader range of applications in the assembly of other mechatronic and electronic products.

VI. CONCLUSION

DT technology bridges the gap between the information and physical worlds and is gaining increasing attention in the field of assembly quality control. This paper introduces an intelligent control model framework based on DT technology for assembly quality prediction. We discuss the relevant modules within the framework, including the physical layer, virtual layer, twin database, communication layer, and service layer. The proposed intelligent control model leverages DT and high-precision prediction algorithm to enhance the quality of the physical assembly process. Furthermore, we provide a process for implementing DT technology in assembly quality control according to the analysis of the EM brake assembly process. To address the lack of quality prediction in the assembly process, we develop the integrated GRA-IPSO-LSSVR prediction algorithm within the intelligent model. The superiority of the algorithm is verified by experiments.

For future work, we plan to optimise and enhance the DT-driven intelligent control model. Moreover, we aim to develop more reliable virtual models and intelligent decision-making methods to make enterprises more adaptable. Additionally, we intend to implement measures to further enhance the predictive accuracy of our models. These measures will include collecting additional manufacturing and assembly parameters and employing a combination of ML and heuristic algorithms. Our future work considers dynamic optimal control of multi-mass characteristic parameters of the manufacturing process using reinforcement learning.

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