PREDICTION OF STANDARD TIME OF THE SEWING PROCESS USING A SUPPORT VECTOR MACHINE WITH PARTICLE SWARM OPTIMIZATION

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Abstract:

Standard time is a key indicator to measure the production efficiency of the sewing department, and it plays a vital role in the production forecast for the apparel industry. In this article, the grey correlation analysis was adopted to identify seven sources as the main influencing factors for determination of the standard time in the sewing process, which are sewing length, stitch density, bending stiffness, fabric weight, production quantity, drape coefficient, and length of service. A novel forecasting model based on support-vector machine (SVM) with particle swarm optimization (PSO) is then proposed to predict the standard time of the sewing process. On the ground of real data from a clothing company, the proposed forecasting model is verified by evaluating the performance with the squared correlation coefficient \( R^2 \) and mean square error (MSE). Using the PSO-SVM method, the \( R^2 \) and MSE are found to be 0.917 and 0.0211, respectively. In conclusion, the high accuracy of the PSO-SVM method presented in this experiment states that the proposed model is a reliable forecasting tool for determination of standard time and can achieve good predicted results in the sewing process.

Keywords:

Standard time, support-vector machine, particle swarm optimization, grey correlation analysis

1. Introduction

In recent years, due to greater competition in the market, the product types have become more diverse and their life cycles shorter. To keep up with the business environment changes, improving the enterprise’s agility and response quickly to the customer’s requirements is becoming more and more important. In such a context, an efficient method for determination of standard time should be explored even further. It is very difficult to prepare manufacturing plans, short- or long-term forecasts, pricing, and other technical or managerial activities in a company without accurate standard time [1]. Standard time not only directly affects the working time and the utilization rate of the equipment, but is also the basic unit for calculating cost and remains widely used for cost management in manufacturing enterprises. Therefore, standard time prediction has direct bearing on economic accounting, production schedule control, resource optimization, production cycle shortening, cost control, and product quotation. Additionally, it ultimately promotes the labor productivity of enterprises and enhances their market competitiveness [2]. Standard time is a common language between fashion brands and manufacturers for discussions on cost, time, and floor capacity. A manager should know the time consumption of a new product processing exactly before acceptance. The term “standard time” is used to refer to time required by an average skilled operator, working at a normal pace, to perform a specified task using a prescribed method [3]. It includes appropriate allowances to allow the person to recover from fatigue and, where necessary, an additional allowance to cover contingent elements which may occur but have not been observed. Since Taylor defined standard time as the most fundamental way to represent productivity under the basic concept of “A Fair Day’s Work”, many methods on the determination of standard time have been performed such as time study, activity sampling, synthetic timing, analytical estimating, and predetermined motion time systems (PTTs) [4]. Chen et al. [5] proposed a synthetic timing method to solve the problem of identifying standard time of a customized part in a mass customization environment. Pan et al. [6] established standard time in the die manufacturing process using an activity sampling method. Wang et al. [7] suggested an estimation procedure of standard time for companies manufacturing multi-pattern and extremely small quantity items. Li et al. [8] used a time study method to establish the man-hour quota calculation model, data structure, and work improvement circulation model for an enterprise specialized in producing nuclear power pipes. Park et al. [9] used the PTS method to establish standard time for agricultural work in Korea.

The joining together of garment components, known as the sewing process, is the most labor-intensive part of garment manufacturing [10]. The sewing process needs to be carried out strictly in accordance with the production plan, which includes not only the distribution of production sites, equipment, and resources but also the arrangement of standard time. Standard time is a key indicator to measure the production efficiency of
the sewing department [11]. There are a great many studies to apply the above-mentioned approach to predict standard time of the process in apparel production. Ye et al. established standard time in garment manufacturing process using the synthetical timing method [12]. Wu et al. proposed an analytical estimating method for standard time based on similarity of sewing processes [13]. Liu et al. [14] performed a traditional time study method by using a stopwatch for a garment producing company [14]. Jinsong et al. [15] made use of the PTSS method to calculate the standard time of the template sewing process [15]. However, these methods have their limitations. For instance, results of the analytical estimating method depend on human knowledge and experience; thus, different people obtain different results for time estimation. The synthetic timing method needs a lot of work to build up books of times, but it is not easy to update those books. PTSS are labor consumption methods, and thus they are not often used in pre-production, especially in small lot production. In this sense, it is essential to explore a reliable, easy to update, and reasonable way for determination of the standard time of the sewing process with efficient apparel manufacturing under such a volatile production environment.

Recently, machine learning techniques, such as artificial neural network (ANN) and support-vector machine (SVM), have been applied for standard time prediction. Advanced methods for determination of standard time can effectively help enterprises to reduce costs and improve production efficiency. Eraslan [1] proposed a new time estimation method based on different robust algorithms of ANNs. Kutschenreiter-Praszkiewicz [16] presented the application of neural network for unit time determination in small batch processing [16]. Chao and Danchen [17] proposed a standard time system based on neural network through the analysis of the characteristics of the standard time table [17]. The ANN has the ability to learn and approach the nonlinear function and has been considered as a powerful computing tool for establishing the mathematical relationship of the nonlinear system based on input-output data. However, the ANN has the following insurmountable shortcomings: lack of a unified mathematical theory, easy to enmesh local minimization, weak generalization ability for the small-sample data set, being prone to overfitting, etc. [18]. SVM was proposed by Vapnik et al. in 1995, and it is based on structural risk minimization (SRM) and Vapnik-Chervonenks dimension principle. Research shows that SVM with many attributes of excellence, such as fast learning, global optimization, and excellent generalization ability for the small-sample data set, is generally superior to the ANN model [19]. It has been studied increasingly in recent years and applied to several standard time formulating problems. Shang et al. [20] put forward an intelligent standard time forecast method and its relevant parameter selection algorithm based on kernel approximation and SVM [20]. Yu et al. [2] established a standard time prediction model based on SVM in the aircraft assembly work and compared its performance with the back propagation neural network. However, there are few related studies using SVM for standard time prediction in the apparel production field.

The main objective of this article is to further develop and improve the application of intelligent technology in the sewing process management, establish a prediction model using the machine learning technique, and optimize model parameters by particle swarm optimization (PSO) to forecast standard time in the sewing process. The remainder of the paper is organized as follows. In Section 2, an overview of the proposed approach is described. Section 3 presents a case study. Section 4 shows comparison analysis and presents some discussions of the results. Section 5 concludes the paper.

2. Methodology

2.1. Basic principle of SVM

A machine learning algorithm called SVM based on statistical learning theory and SRM principle performs well for classification and regression properties [21]. Thus, SVM can be divided into support-vector classification machine and support-vector regression machine. The former usually deals with classification problems, and the latter is used for prediction. The purpose of support-vector regression machine is to analyze the function \( y_i = f(x_i) \) between the input and output according to the given training sample \((x_1,y_1),(x_2,y_2),\ldots,(x_n,y_n)\). Assuming the function is \( f(x) \), the output \( y' \) is the regression value based on the regression function. It is clear that standard time forecasting belongs to the typical nonlinear problem. The input variables are mapped into a high-dimensional linear feature space through a nonlinear transformation \( \phi(x) \). The regression function in high-dimensional space, which represents the relationship between standard time of the sewing process and input variables, can be defined as follows: \( f(x) = \omega \cdot \phi(x) + b \), where \( \omega \) is the weight vector and \( b \) is bias. The values of \( \omega \) and \( b \) can be obtained by using the following minimization equation, where \( \xi_i \) and \( \xi_i^{*} \) are relaxation factors, and \( \|\omega\|^2 \) represents the confidence range to smooth the fitting function and strengthen the promotion ability of fitting function. The constant \( c \) is a penalty coefficient when the training data are out of the channel, and it can penalize the error by determining the trade-off between the training error and the model complexity. The larger value of \( c \) represents the hard-margin regression function, while the smaller value indicates that the estimation function allowed deviating from \( \varepsilon \) with a lower cost. If the regression function \( f(x) \) can estimate all the training sample points, the minimization problem could be transformed into the following optimization problem:

\[
\begin{align*}
\min \left[ \frac{1}{2} \|\omega\|^2 + c \sum_{i=1}^{n} (\xi_i + \xi_i^*) \right] \\
\text{s.t.} \quad y_i - \omega \cdot \phi(x_i) - b \leq \varepsilon + \xi_i \\
\omega \cdot \phi(x_i) + b - y_i \leq \varepsilon + \xi_i^* \\
\xi_i \geq 0, \quad \xi_i^* \geq 0, \quad i = 1,2,\ldots,n
\end{align*}
\]

Since Eq. (1) is a convex optimization problem, the LaGrange multipliers will be introduced to obtain the LaGrange function. Then, the original problem could be transformed into the
corresponding dual problem and the regression function can be obtained as follows:

\[
    f(x) = \sum_{i=1}^{n}(a_i - a_i^*)K(x_i, x) + b^*  
\]

(2)

where \(a_i\) and \(a_i^*\) are the LaGrange multipliers, which are automatically selected by the SVM algorithm during development of the model. In Eq. (2), \(K(x_i, x)\) is a kernel function, which attempts to fit a tube in a higher dimensional space. There are four commonly used kernel functions, i.e., radial basis kernel, sigmoid kernel, polynomial kernel, and linear kernel. Choosing different kernel functions can generate different SVM models. In this paper, the radial basis kernel was utilized: \(K(x_i, x) = \exp(-\frac{|x_i - x|^2}{\sigma^2})\), where the free parameter \(\gamma\) is the kernel parameter.

2.2. Parameter optimization of the SVM model based on PSO

The SVM model has a good ability to solve small-sample, high-dimensional, and nonlinear problems. However, the choice of kernel function parameter \(\gamma\) and the penalty parameters \(c\) of the SVM model have important influences on the accuracy of the SVM model. Only by constantly adjusting the model parameters to achieve the best combination of model parameters can the SVM machine learning ability and regression prediction effect be improved. Therefore, the penalty parameters \(c\) and kernel parameters \(\gamma\) should be optimized. The traditional methods of SVM parameter selection are generally the cross validation method and grid search method. These two methods have some limitations: low efficiency, low precision, and the fact that the search parameters cannot be optimized. PSO is a new evolutionary algorithm developed in recent years, and it was inspired from the feeding behavior characteristic of a bird flock, which is used for solving the optimization problems [22]. In the PSO algorithm, a group of particles was initialized in the feasible solution space, each potential solution to the problem was treated as a particle, and the common feature of the particle is represented by position, speed, and fitness value. The fitness value is calculated by the fitness function, which is worthy of the pros and cons of the said particle. In the D-dimensional space, the space vector \(X_i = (X_{i1}, X_{i2}, \ldots, X_{id})^T\) is represented as the \(i\)th particle, where \(i = 1, 2, \ldots, n\) ( \(n\) population quantity) and \(X_i\) is the position of the \(i\)th particle and a possible solution. After finding the local and globally optimal solutions, the particle would update its speed and new position according to the following equation:

\[
    V_{id}^{k+1} = wV_{id}^k + c_1r_1(P_{id} ^k - X_{id}^k) + c_2r_2(P_{gd} ^k - X_{id}^k)  
\]

(3)

\[
    X_{id}^{k+1} = X_{id}^k + V_{id}^{k+1}  
\]

(4)

In the formula, \(k\) is the \(k\)th iteration; \(V_i = (V_{i1}, V_{i2}, \ldots, V_{id})\) is the velocity of the \(i\)th particle, and \(P_i = (P_{i1}, P_{i2}, \ldots, P_{id})\) is the optimal position of this particle. The optimal swarm position is \(P_g = (P_{g1}, P_{g2}, \ldots, P_{gd})\). Under the condition of the \(i\)th particle at the \(k\)th iteration, \(V_{id}^k\) and \(X_{id}^k\) are the \(id\) speed component and location, respectively. Parameters \(r_1\) and \(r_2\) are the random number, the range is 0–1, \(c_1\) and \(c_2\) are the learning factors between 0 and 2, and \(w\) is the inertial weight of the PSO algorithm. To prevent the particle disengaging from the search space in the search process, \(V_{id} \in [-V_{max}, V_{max}]\), where \(V_{max}\) is the maximum flying speed. To speed up the convergence of the algorithm, \(w\) is linearly reduced as the iteration progresses:

\[
    w = \frac{w_{max} - iter(w_{max} - w_{min})}{iter_{max}}  
\]

(5)

where \(iter\) and \(iter_{max}\) are the current and maximum iteration times, respectively; and \(w_{max}\) and \(w_{min}\) are the maximum and minimum inertial weights, respectively [19].

The process of using PSO for parameter optimization is as follows:

1. The population is initialized. The population size, the maximum number of iterations of the population, the penalty factor \(c\), and the optimization range of the kernel parameter \(\gamma\) are set. The learning factors \(c_1\) and \(c_2\) are adopted by the linear learning strategy. The inertial weight \(w\) is adopted by the linear decreasing strategy.

2. The position \(x_i^0\) and velocity \(v_i^0\) of the initial particles within the allowed range are generated randomly.

3. The fitness calculation is carried out by assigning the mean squared error (MSE) as the fitness value when cross-checking the training set.

4. The fitness value \(f_i\) of the current position of each particle in the population with the individual extreme value \(p_{best}\) is compared; if \(f_i < p_{best}\), then \(p_{best} = f_i\), otherwise \(p_{best}\) remains unchanged.

5. The individual optimal value \(p_{best}\) of each particle in the population with the population global extremum is compared; if \(p_{best} < g_{best}\), then \(g_{best} = p_{best}\), otherwise \(g_{best}\) remains unchanged.

6. If the termination condition is satisfied, the iteration is stopped and the positional parameters of the optimal particle are output; that is, the optimal penalty coefficient \(c\) of the SVM and the kernel function parameter \(\gamma\) are output; otherwise, steps 3–6 are repeated.

2.3. Framework for standard time prediction of the sewing process based on the PSO-SVM method

Stage 1: Identify the influencing factors of standard time in the sewing process

Input measures for machine learning algorithms are often referred to as influencing factors. The SVM model learns the relation between the influencing factors and the output values. In order to obtain the influencing factors of standard time in the sewing process more comprehensively, we conducted expert interview and literature analysis [23–29] to select the
relevant core influencing factors. Experts were selected by a
typical sampling method, and an open questionnaire was used to
doctor in-depth interviews. A total of 13 interview records
were obtained. The profile of these 13 interviewees is shown in
Table 1.

In general, many objective or subjective factors are involved in
the complicated apparel manufacturing process. Based on the
in-depth analysis of the relevant literature on the influencing
factors of standard time in the sewing process, the influencing
factors generally considered more important in most studies
were extracted. First, the complexity of a garment sewing
process is determined primarily by clothing style, such as type
of fabric, type of seams, and the size and shape of cutting
patterns. Yukari et al. [29] studied the relationship between
the seam ability and mechanical properties of wool fabrics
and showed that the mechanical properties of fabrics affect
the quality and difficulty level of garment productions. Second,
stable garment manufacturing processes require advanced
production equipment and a good production condition. Third, workers’ level of effort and skill proficiency directly
impact production efficiency and actual standard time in
garment manufacturing. It is well demonstrated in the apparel
industry that providing training for new workers or offering pre-
production process is effective to improve workers’ ability to
operate the equipment. Finally, a professional management
team and management practices also affect the standard time
in the sewing process. Higher wages or rewards motivate
workers to maintain high levels of effort, encourage them to
keep work interests, and enable them to develop relationships
with managers or colleagues. Before making the prediction, the
grey correlation analysis method was adopted to confirm the
main influencing factors of standard time in the sewing process.

Stage 2: Construction of the PSO-SVM prediction model.

A multi-input and single-output support-vector regression model
is formulated by constructing the relationship between the input
and the output through the SVM model. The establishment
of the standard time prediction model of the sewing process
mainly includes training and testing. Firstly, sewing process
cases are collected as sample data; then, the processed
data samples are selected randomly as training sets, and the
remaining samples are used as test sets. Secondly, the PSO
algorithm is used to optimize the model parameters, which can
be derived according to Eqs (3)–(4), and the training set is used
to learn the SVM model. To this end, the relationship between
standard time in the sewing process and factors that influence
sowing can be established, and the continuous standard time
could also be predicted by this. The flowchart of the framework
is presented in Figure 1.

3. Case studies

3.1 Data description and preparation

The raw data were adapted from ZS Company, which is a
privately held family owned clothing company based in China.
The company was founded in 1989, owning four fashion
brands, and has accumulated a great amount of sewing standard time data during its multiple years of production. After
cleaning the data to remove incomplete records, the final data
set consists of 105 sewing processes, including standard time
and influencing factors, as shown in Table 2.

In order to eliminate the influence of data dimensions on the
prediction results, the original data need to be preprocessed.
The dimensionality reduction method used in this paper is the
minimum–maximum (min–max) method, and the calculation
formula is expressed as follows:

![Figure 1. The PSO-SVM prediction model flow of standard time in
the sewing process. PSO, particle swarm optimization; SVM, support-
vector machine.](http://www.autexpj.com/)

| Characteristic          | Number | Percentage |
|-------------------------|--------|------------|
| Gender                  |        |            |
| Male                    | 6      | 46.2%      |
| Female                  | 7      | 53.8%      |
| Age                     |        |            |
| 26–35 years             | 4      | 30.8%      |
| 36 years and above      | 9      | 69.2%      |
| Educational background  |        |            |
| Undergraduate           | 10     | 76.9%      |
| Graduate                | 3      | 23.1%      |
| Occupation              |        |            |
| Enterprise administrator| 10     | 76.9%      |
| Researcher              | 3      | 23.1%      |

http://www.autexpj.com/
where $x_i$ is the $i$th item in the sequence; $x_{\text{min}}$ is the minimum value of the sequence; and $x_{\text{max}}$ is the maximum value of the sequence. The significance of min–max dimensioning is to project the whole sequence onto the $[0,1]$ interval in the process of dimensioning the sequence, where the projection process does not change the scale relationship between the sequence items.

### 3.2 Selection of influencing factors of standard time in the sewing process

Influencing factors are input data for machine learning algorithms. During the sewing process, as mentioned above, many factors affect the standard time, such as sewing length, stitch density, bending stiffness, fabric weight, production quantity, drape coefficient, and length of service. Before making the prediction, the main influencing factors of standard time in the sewing process were identified by grey correlation analysis. Grey correlation analysis aims to quantitatively describe the relationship or development trend between variables according to the correlation degree. The reference sequence reflecting the system’s behavior characteristics and the comparison sequence affecting the system’s behavior are both supposed to be determined. The data sequence that reflects the behavior characteristics of the system is called reference sequence. The data sequence composed of factors that affect the system’s behavior is called comparison sequence [30]. If the correlation degree between the comparison sequence and the reference sequence is large (correlation degree > 0.6), the relationship between the two is considered to be close; on the other hand, if the correlation degree is small (correlation degree < 0.5), the relationship between the two is distant. This is used as the basis to judge the correlation. The grey correlation coefficient $\xi(ij)$ of the reference sequence and the comparison sequence is computed and given as follows:

$$\xi(ij) = \frac{\min_{1 \leq i \leq n} \max_{1 \leq j \leq m} |x_{ij} - x_{ij}| + \max_{1 \leq j \leq m} \min_{1 \leq i \leq n} |x_{ij} - x_{ij}|}{\max_{1 \leq j \leq m} \max_{1 \leq i \leq n} |x_{ij} - x_{ij}|}$$  

Table 2. Influencing factors and standard time of the sewing process.

| No. | Standard time (s) | Sewing length (cm) | Stitch density (cm) | Bending stiffness (cN·m) | Fabric weight (g/m²) | Production quantity (piece) | Drape coefficient (%) | Length of service (number of years) |
|-----|------------------|--------------------|---------------------|-------------------------|---------------------|-----------------------------|---------------------|-----------------------------------|
| 1   | 25               | 24                 | 6                   | 1.558 × 10⁻⁷           | 79                  | 500                         | 21                  | 4                                 |
| 2   | 64               | 100                | 5                   | 5.503 × 10⁻⁷           | 99                  | 260                         | 33                  | 3                                 |
| 3   | 58               | 48                 | 5                   | 7.769 × 10⁻⁷           | 106                 | 665                         | 40                  | 3                                 |
| 4   | 23               | 30                 | 5                   | 9.357 × 10⁻⁷           | 110                 | 320                         | 44                  | 9                                 |
| 5   | 32               | 48                 | 5                   | 4.333 × 10⁻⁷           | 50                  | 680                         | 41                  | 3                                 |
| 6   | 41               | 100                | 6                   | 9.216 × 10⁻⁷           | 109                 | 345                         | 41                  | 5                                 |
| 7   | 32               | 44                 | 5                   | 4.839 × 10⁻⁷           | 93                  | 260                         | 30                  | 3                                 |
| 8   | 42               | 32                 | 5                   | 7.247 × 10⁻⁷           | 99                  | 708                         | 39                  | 4                                 |
| 9   | 69               | 152                | 5                   | 7.514 × 10⁻⁷           | 105                 | 652                         | 39                  | 3                                 |
| 10  | 71               | 204                | 5                   | 9.011 × 10⁻⁷           | 112                 | 380                         | 42                  | 5                                 |
| 11  | 49               | 160                | 5                   | 1.683 × 10⁻⁷           | 72                  | 135                         | 19                  | 6                                 |
| 12  | 30               | 10                 | 4                   | 4.893 × 10⁻⁷           | 94                  | 260                         | 31                  | 5                                 |
| 13  | 51               | 92                 | 5                   | 7.268 × 10⁻⁷           | 102                 | 526                         | 36                  | 3                                 |
| 14  | 33               | 53                 | 6                   | 9.115 × 10⁻⁷           | 108                 | 264                         | 39                  | 5                                 |
| 15  | 27               | 12                 | 6                   | 9.115 × 10⁻⁷           | 108                 | 264                         | 39                  | 5                                 |
| 16  | 30               | 65                 | 5                   | 4.012 × 10⁻⁷           | 46                  | 380                         | 36                  | 2                                 |
| 17  | 32               | 40                 | 5                   | 7.869 × 10⁻⁷           | 84                  | 246                         | 41                  | 5                                 |
| 18  | 51               | 92                 | 5                   | 6.589 × 10⁻⁷           | 90                  | 342                         | 36                  | 3                                 |
| 19  | 15               | 10                 | 5                   | 4.379 × 10⁻⁷           | 88                  | 268                         | 28                  | 4                                 |

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105 9 5 6 3.998 × 10⁻⁷ 76 260 27 3
When we input the \( p \)-identification coefficient, ordinary \( p \) gets 0.5. The correlation degree \( r_{0i} \) formula is as follows:

\[
r_{0i} = \frac{1}{n} \sum_{j=1}^{n} \xi(j) \quad i = 1, 2, 3, 4, 5, 6, 7
\]

where \( r_{0i} \) is the grey correlation degree of the sequence \( x_i \) to the reference sequence \( x_0 \). The closer \( r_{0i} \) is to 1, the better is the correlation.

The standard time in the sewing process was taken as the reference sequence, and the influencing factors are the comparison sequences. MATLAB can be used to calculate the related grey correlation degree. According to Table 3, the influencing factor with the maximum correlation degree for the standard time of the sewing process is the sewing length (0.823), and the influencing factor with the minimum correlation degree is the seam density (0.613). When the grey correlation degree is 0.6–1.0, there is a high degree of correlation between the reference sequence and the comparison sequence; when the grey correlation degree is 0.6–0.8, the reference sequence and the comparison sequence have a relatively high degree of correlation; when the grey correlation degree is <0.5, the correlation between the reference sequence and the comparison sequence is weak. Because none of the influencing factors is <0.6, this paper selects the above seven factors as the input vector of SVM.

### 3.3 Construction of the PSO-SVM model for prediction of standard time in the sewing process

A total of 105 samples were collected in the construction of the standard time prediction model of the sewing process. In this case study, 88 samples were selected randomly as training samples, and 17 samples were used as testing samples to train and test the PSO-SVM model. The MATLAB and LIBSVM toolbox were used to implement the SVM model according to the construction process. When the PSO-SVM program was written, the initial parameters of the model were set. The standard PSO with 20 particles (SIZEPOP = 20) and 200 iterations was used (MAXGEN = 200). The value range of \( \gamma \) was (0.01, 1,000) and \( c \) was (0.1, 150). In PSO, the learning factor was a random number between 0 and 2. In this paper, the learning factors were \( c_1 = 1.2 \) and \( c_2 = 1.5 \). The machine environment was an i5-2430M central processing unit (CPU) with a frequency of 3.90 GHz and a memory of 4.0 GB, running on the Windows 7 operating system. After initialization, the calculation program was processed to read the sample data of the training set. The kernel parameter \( \gamma = 0.01 \) and penalty parameter \( c = 101 \) of SVM were obtained.

4. Results and analysis

#### 4.1 Performance analysis

For the sewing process, the PSO-SVM model with radial basis kernel function is introduced to predict the standard time. MSE and squared correlation coefficient \( (R^2) \) are introduced as performance criteria for prediction assessment. The comparison between the actual and predicted values in the training set is shown in Figure 2. In Figure 2, x-axis represents the sample size of the training set, and y-axis the standard time of the sewing process. Then, the regression prediction was made for the test data of randomly selected test samples. The comparison between the actual value and the predicted value is shown in Figure 3. As shown in Table 4, in the training experiment, the \( R^2 \) criterion is 0.917. In the testing experiment, the \( R^2 \) is 0.852. Irrespective of whether the process involved is the training data experiment or testing data checking, the prediction model of the standard time of the sewing process based on PSO-SVM optimization algorithm achieves higher prediction performance. Therefore, the prediction model of PSO-SVM has excellent generalization ability and can obtain a scientific prediction result for standard time of the sewing process.

![Figure 2. Comparisons of actual values and predicted values of the training set.](http://www.autexrj.com/)  

![Figure 3. Comparisons of actual values and predicted values of the test set.](http://www.autexrj.com/)
Table 4. Performance of the PSO-SVM model.

|              | MSE    | $R^2$  |
|--------------|--------|--------|
| Training samples | 0.0211 | 0.917  |
| Test sample   | 0.0844 | 0.852  |

MSE, mean square error; PSO, particle swarm optimization; SVM, support-vector machine.

In order to further validate the performance of the model, we also presented a BP neural network to make a prediction experiment. The forecasting result is shown in Figure 4. As shown in Table 5, MSE of the BP neural network is much higher than that of SVM, and $R^2$ of SVM is closer to 1. It is obvious that the prediction result of SVM is much better than that of the BP neural network. Thus, it is proven that SVM can be effectively applied to the prediction problem of a small sample while maintaining sufficient accuracy.

4.2 Comparison of results of different parameter optimization methods

In the SVM theory, determining the model parameters such as penalty parameter $c$ and kernel function parameter $\gamma$ is a very important step in the process of model establishment. The conventional parameter search method is the cross validation method for SVM. The basic idea of cross validation is that we usually do not use all the data sets for training, but use part of it (this part does not participate in the training) to test the parameters generated by the training set, and relatively objectively judge the parameters of the data outside the training set. For the PSO-SVM optimization algorithm, parameter optimization is obtained by judging the individual extremum and global optimal solution of the particle, as well as adjusting the velocity and position of the particle. Training data is conducted with different model parameters and verified on the validation set to determine the most appropriate model parameters. Table 6 shows the model performance based on different parameter search methods. As demonstrated in Table 6.

Table 6. Comparison of the prediction results with different parameter optimization methods.

| Optimization algorithm | Parameters | MSE  |
|------------------------|------------|------|
| PSO                    | 101 0.01   | 0.0358 |
| Cross validation       | 128 0.01   | 0.1157 |

MSE, mean square error; PSO, particle swarm optimization.

6 from the MSE results, it could be observed that the SVM-derived result with the model parameters selected by PSO has better performance than those of the cross validation methods. Therefore, it can be concluded that the PSO-SVM method has a better model prediction capability than the ordinary SVM method based on cross validation.

5. CONCLUSIONS

This study includes seven independent variables identified as the influencing factors of standard time in the sewing process, which are sewing length, stitch density, bending stiffness, fabric weight, production quantity, drape coefficient, and length of service. By means of the grey correlation analysis, the results showed that there is a significant correlation between the seven factors and the standard time of the sewing process. The MSE and $R^2$ have been used to measure the effectiveness of the model in predicting standard time. It was found that the model in this study can predict the standard time of the sewing process quickly and accurately. By comparing the cross validation parameter selection method, it can be proven that the PSO algorithm performs better among the tested methods on the basis of higher accuracy.

In the production of apparel manufacturers, especially for the sewing process, experience is often used to estimate the standard time, which is subjective and lack of scientific basis. Although a large amount of data has been accumulated in production, it cannot be combined with the results. As a machine learning model, the proposed PSO-SVM method can establish the potential relationship between the influencing factors and the standard time. With the development and accumulation of big data in the apparel industry, the managers are able to apply the proposed prediction model to obtain a more accurate result for the standard time in the sewing process.

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