# Dynamic Cost Estimation of Reconstruction Project Based on Particle Swarm Optimization Algorithm

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*Abstract: This paper proposes the research on dynamic cost estimation of reconstruction project in accordance with the particle swarm optimization procedure in order to predict the value of dynamic cost estimation of reconstruction project. To accomplish the task initially the applicability of example swarm optimization procedure is introduced. The basic principle of particle swarm optimization procedure is described, and PSO (particle swarm optimization) procedure is used to optimize the super factors of LS- SVM. The spss20.0 statistics is used to cluster the sample data to obtain similar engineering classes. BP-NN (Back Propagation Neural Network), LS - SVM, and PSO-LSSVM are implemented to anticipate and simulate the development price for the authentication of request effect of the optimized design in that area. The results show that the relative errors of the three designs are controlled within + 10%, this may be used in the early stages of building to anticipate construction costs accurately. The range of the relative error dissemination interval predicted using the BP-NN design is 13.12% and is between [- 7.46%, 5.74%]. The range of the relative error dissemination interval predicted by the LS SVM design is 14.22% and is between [-8.12%, 6.17%]. According to the PSO-LSSVM design, the relative error dissemination interval is [-2.56%, 2.49%], and its range is 5.21%. In terms of prediction stability and robustness, the prediction design optimized using PSO procedure outperforms the LS SVM design. In conclusion, the predictions design on the basis of PSO optimized LS SVM is better appropriate for predicting construction costs early in the building process and has strong guiding importance for the cost of construction.*

*Povzetek: Raziskava predlaga dinamično ocenjevanje stroškov obnove projektov z uporabo postopka optimizacije delcev za natančnejše napovedi.*

## 1 Introduction

Cost prediction has an impact on project cost and project plan, and plays a significant role in the field of project management. Therefore, project cost prediction has always been the focus of attention [1]. In the process of project cost prediction, due to the influence of many factors, the designing process of project cost prediction is very complex. Therefore, project cost prediction is also a difficulty in the research of project management and has become an important research direction [2]. At present, the project cost prediction design can be divided into two categories: traditional design and modern design. The traditional design mainly includes quota method, bill of quantities method and so on. The quota method predicts the project cost according to the released budget quota. The project cost prediction result of the design will not be too low or too high, and the prediction error is small. However, this method does not consider market competition factors, human factors and technical improvement factors, and the efficiency of designing and prediction is very low, which is not suitable for the cost prediction of large projects [3]. The bill of quantities method is proposed for the deficiency of the quota method. In practical request, due to the failure to consider the vicious competition between enterprises, the error of project cost prediction is large and the defect is very obvious [4]. Modern project cost prediction designs are divided into two categories: linear design and nonlinear design. The linear design mainly includes fuzzy mathematical design and multiple linear regression design. The change of project cost has certain randomness and nonlinearity, while the linear design cannot describe the nonlinear change characteristics of project cost, and the prediction error of project cost is high. Figure 1 shows the preparation process of construction project investment estimation [5].

When planning a project, by devoting more resources to tasks, the time of the project might be shortened. However, restricting the duration of projects below their standard level is associated with additional costs. The time-price trade-off problem (TCTP) objective is to find a collection of time-cost options that, in specific circumstances, yield the best scheduling [6]. Many studies have concentrated on a discrete variant of this problem, known as the discrete time-cost trade-off problem (DTCTP), because in practice many resources (such as workers and equipment) are accessible in discrete increments [7]. Cost optimization problems, time optimization problems, and Pareto front problems are the three main forms of DTCTP that are frequently discussed in the literature. A cost optimization issue aims to identify a collection of time cost alternatives that would

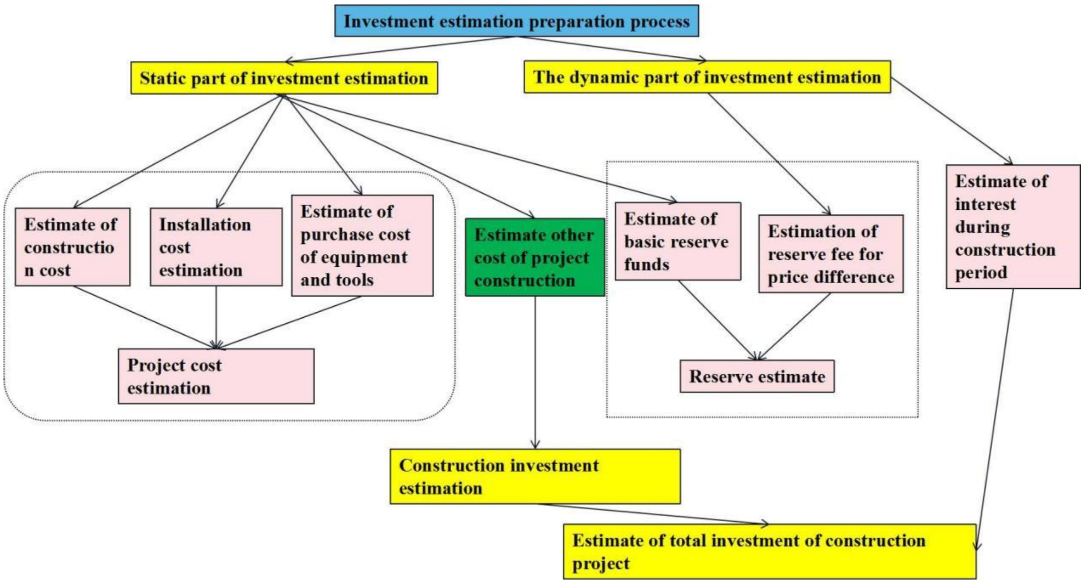



Figure 1: Preparation process of construction project investment estimation.

reduce overall cost under specific constraints, such as given a hard project deadline or penalty for delays. The objective of the budgeting problem is to find time-cost alternatives to shorten the project's timeline while staying within the allocated budget.

The remainder of this essay is structured with a section 2 devoted to literature and a section 3 devoted to research methodologies. Results are shown in Section 4, and the conclusion is offered in Section 5.

## 2 Related work

This section contains a variety of cutting-edge works in the topic of cost estimate of reconstruction project based on several procedures are discussed.

In view of this research problem, Chen *et al.* start with analyzing the disadvantages of the traditional project cost management system, discuss the necessity, inevitability and realistic environment of implementing bill of quantities pricing in China, and expounds the concept, content, characteristics and preparation methods of bill of quantities, especially how construction enterprises prepare enterprise quota and quotation. In addition, the supporting environment required for the implementation of bill pricing is discussed [8]. Shi *et al.* made an in-depth and detailed analysis on the project cost activities under the bill of quantities pricing mode, made a detailed analysis and Discussion on the project cost control in each stage, and established and improved the project cost management system under the bill of quantities pricing mode [9]. Based on the valuation of bill of quantities and the analysis of project cost composition, Ullah *et al.* put forward the object and content of project cost management in the implementation stage and the management measures in each stage [10]. Peng *et al.* introduced the characteristics and implementation significance of the bill of quantities pricing, and discussed the content, characteristics and precautions of cost management under the bill of quantities pricing mode [11]. Based on the viewpoint of active control, Yan *et al.* systematically analyzed various problems existing in the cost management process of construction projects, analyzed in detail the cost management objectives and main contents of construction projects in different stages, and put forward the measures and methods of whole process cost management, so as to establish the whole process cost management system [12]. Jing *et al.* control the total cost of the project through satisfaction. Because design is an important factor to determine the project cost. Taking the technical route of comprehensive cost management and taking the four aspects of the whole process, the whole risk, the whole team and the whole factor cost management as the starting point, this paper puts forward relevant suggestions and measures for cost management in the design stage, in order to achieve better control effect of project cost [13]. Based on the research and analysis of the whole process, whole life cycle and total cost management, Nanchian *et al.* put forward the cost management theory and method suitable for China's government investment projects, and established the evaluation design for the investment scheme [14]. Ivanov *et al.* discussed in detail and studied the design of cost and quality control objectives in life cycle management [15]. Akimov and Matasov discussed some problems existing in cost control in the design stage of power transmission and transformation project. Combined with the engineering practice of power grid project, this paper analyzes and puts forward relevant measures to control the cost from the aspects of technology, management and system. It is considered that based on the trinity of technology, management and system, a project cost control system of "reasonable scheme, controllable investment and cost saving" should be established in the design stage [16]. Based on the current research, this paper puts forward the research on dynamic cost estimation of reconstruction project based on particle swarm optimization procedure. Firstly, the applicability of example swarm optimization procedure is introduced. The basic principle of particle swarm optimization procedure is described, and PSO (particle swarm optimization) procedure is used to optimize the super factors of LS-SVM. With the help of spss20.0 to cluster the sample data to obtain similar engineering classes. LS-SVM, PSO-LSSVM, and BP neural networks are used to simulate and estimate the project price for better assessing the request effect of the optimized design in that area. The experimental results verify the efficiency and accuracy of the prediction design on the basis of PSO optimized LS SVM.

# 3 Research methods

The design process, fundamental principles, and particle swarm optimization technique are covered in this section.

## 3.1 Applicability investigation of the particle swarm optimization technique

Particle swarm optimization (PSO), which was developed to find the global optimal solution to the optimization issue, was first motivated by the foraging behavior of birds. The law of this biological group movement is that assuming that the birds are randomly foraging in an area, and the birds do not know the specific location of the food, but they can perceive the distance between the food and their current location, the best foraging strategy is to search around the birds closest to the food. Unlike genetic algorithm (GA), PSO procedure does not rely on the evolutionary idea of individual survival of the fittest, but simulates swarm intelligence behavior and finds the global optimal solution through competition and cooperation among individuals [17]. In PSO procedure, the possible solutions of all target problems are in d-dimensional space, and each solution is equivalent to a "bird", which is called "division". The current position of the division is determined by the objective function, and its fitness value can be obtained. On the one hand, each division relies on its own experience to remember its best position, on the other hand, it perceives the best position of divisions other than itself according to the experience of its peers. Combining these two experiences, each division follows the division in the current optimal position at a speed that determines its distance and direction. The velocity of divisions is constantly updated with the change of relevant information, so that the position of divisions is dynamically adjusted at any time until a certain condition is reached, then the procedure is considered to obtain the optimal solution. The PSO method has a straightforward structure, a wide search space, and quick convergence. It can solve the majority of global optimal solution problems. The particle swarm may share the historically optimal division positions with one another during the optimization phase of the goal issue since it has memory. At the same time, there aren't any laborious mathematical processes like crossover and mutation, and there aren't any too complicated factors that have to be defined. It has outstanding advantages compared with other swarm intelligence procedures [18]. The integration with other intelligent procedures is a key development trend for the PSO procedure, which has currently moved beyond its original focus on function optimization to include more general requests like pattern recognition and neural network training. The super factor $\sigma$ and $C$ setup for the LS SVM procedure is a critical optimization challenge. As a result, PSO is used in this study to optimize the LS SVM factors and increase the design's ability to predict outcomes accurately [19].

## 3.2 Basic principle of particle swarm optimization

The prime goal of the PSO method is to prepare the position and motion of a collection of casual divisions and, given specific constraints, to continuously iteratively seek for the best solution. The division modernizes its speediness and position in the following round of repetition in accordance with the changes of the two if the finest position passed by each division in the examination procedure is defined as the individual extreme price P_best and the top location found by the current entire group is defined as the global extreme value G_best [20].

Equation 1 and 2 provides a mathematical representation of the particle swarm optimization approach. Assume that a population of m divisions indicating a potential solution to the issue can exist in a d-dimensional search space.

$$X = \{X_1, X_2, ..., X_m\} \tag{1}$$

Among them,

$$X_i = \{x_{i1}, x_{i2}, ...x_{id}\} \tag{2}$$

Signifies the position of the $i^{th}$ division in space, and the corresponding fitness can be calculated by substituting $X_i$ into the goal function connected to the issue at hand. Equations 3 and 4 describe how fast this division will travel in the d-dimensional search space.

$$V_i = \{v_{i1}, v_{i2}, ..., v_{id}\} \tag{3}$$

Use:

$$P_i = \{P_{i1}, P_{i2}, ..., P_{id}\} \tag{4}$$

To represent the best position $P_{best}$ searched by the division itself (the corresponding fitness value is the smallest) by using Equation 5.

$$P_g = \{P_{g1}, P_{g2}, ..., P_{gd}\} \quad (5)$$

To represent the best position $G_{best}$ of the whole population, the velocity and position of the i-th division are updated by Equations 6 and 7 respectively.

$$v_i^{k+1} = \omega v_i^k + c_1 r_1 \left(P_i^k - X_i^k\right) + c_2 r_2 \left(P_g^k - X_i^k\right) \quad (6)$$

$$X_i^{k+1} = X_i^k + v_i^{k+1} \quad (7)$$

Where $\omega$ is the weight of inertia and K is the quantity of iterations; $c_1$ and $c_2$ indicate, what are referred to as knowledge variables, the steps that divisions take to reach their ideal location while flying and their total optimal position; $r_1$ and $r_2$ are two randomly chosen numbers among [0,1]. According to the observation formula (6), essentially, there are three components to the velocity update formula: first, $\omega v_i^k$ indicates the speed of the $i^{th}$ division during the earlier time period, that's referred to as the inertia component. Next, $c_1 r_1 (P_i^k - X_i^k)$ indicates the gap between the ideal location of the $i^{th}$ division and its present location, which is its own experience, is referred to as the cognitive portion; Lastly, $c_2 r_2 (P_g^k - X_i^k)$ depicts the distance between the group's ideal location and the current position and the $i^{th}$ division, it develops from peer experience and represents collaboration and information exchange amongst division groups, and is referred to as the social aspect. In this manner, the division's location in the $K + 1$ using the formula above, iteration may be calculated [21]. The pace is typically restricted to prevent doing an excessive amount of blind searching for divisions $[-v_{max}, v_{max}]$ and the search space is limited to $[-x_{max}, x_{max}]$.

## 3.3 Parameter setting of particle swarm optimization procedure

The PSO procedure needs to have a few factors changed, but reasonable factor setting will also affect its optimization ability and efficiency. Based on extensive reference to relevant literature, this paper obtains the value range of main factors in PSO as follows:

### 3.3.1 Population size and division dimension

When the population size is too large, the optimization performance of PSO procedure will be enhanced, but at the same time, the convergence speed will be reduced. If the population size is too small, the procedure is easy to fall into local optimization and difficult to jump out. In general, 20 ~ 40 divisions are enough. For special problems such as multi-objective optimization, the group size can be 100 ~ 200 85. The division dimension depends on the specific optimization objective, which is generally the dimension of the solution space of the objective optimization problem.

### 3.3.2 Inertia weight factor $\omega$

Inertia weight factor $\omega$ can efficiently strike a balance between local and global search capabilities. It is mainly used to control the influence of the current flight speed of divisions on the next speed, which is conducive to the procedure to fewer iterations are needed to reach the ideal answer. When the $\omega$ value is small, it is convenient for local search, and when the $\omega$ value is large, it is convenient for global search [22]. The results show that when the maximum speed is small, the optimization effect is better when the value of $\omega$ is approximately 0.9, while when the maximum speed is large, the value of 0.4 is better.

### 3.3.3 Termination conditions

Usually, when the fitness value of the procedure reaches the maximum value or meets a preset maximum number of iterations, the procedure calculation ends.

### 3.3.4 Knowledge factors $c_1$ and $c_2$

Knowledge factors $c_1$ and $c_2$ represent the weights of divisions moving near the optimal position of individuals and groups. Through the setting of knowledge factors, divisions can self review and actively learn other excellent individuals in the group, so as to continuously approach the optimal solution. Generally, the values of $c_1$ and $c_2$ are within the range of [0,4], and $c_1 = c_2$.

The following situations need to be explained:

When $c_1 = c_2 = 0$, the division keeps flying at a uniform speed until the boundary of the problem, so the search area is limited and it is difficult to find the solution;

When $c_1 = 0$ and $c_2 \neq 0$, the divisions lack the cognitive part, move to the $G_{best}$ position, and tend to be locally optimal;

When $c_1 \neq 0$ and $c_2 = 0$, the divisions lack the social part, lack the shared information and cooperation in the group, and basically cannot obtain the optimal solution.

## 3.4 Optimization process of particle swarm optimization procedure

The specific calculation stages of the PSO method may be summed up as follows in accordance with the main concept of following the current optimal position division:

i. Set the necessary algorithmic factors, such as the element swarm size and the inactivity weight feature $\omega$, knowledge elements $c_1$ and $c_2$ and close conditions.
ii. Initializing the population, setting the location and velocity vectors to random values of each division in the search space.
iii. Calculate the fitness value $fitness(i)$ of divisions, and find the historical optimal position $P_{best}(i)$ and the current ideal location $G_{best}$ of each division.

iv. According to equations (6) and (7), adjust the division positions and velocities.

v. Determine the fitness value for each division following an update to its speed and position, and then contrast it with the fitness value corresponding to that division's historically best position $P_{best}(i)$. Use the most recent change to the position if the current fitness value is higher $P_{best}(i)$.

vi. A comparison between each division's fitness value and the fitness value corresponding to the global ideal location $G_{best}$ is made. When the global ideal position $G_{best}$ greater than the present ability value, which is modified to reflect the location of the current division.

vii. Check whether the optimization result meets the termination conditions. If not, go back to step (3) and carry out the iteration again. Otherwise, output the $P_{best}$ as the overall best answer and halt the search, equivalent to the current fitness rating.

## 3.5 Optimization of key factors of LS - SVM based on PSO

To apply the PSO technique to improve the LS SVM's super factors, two important contents need to be considered in the fusion process of the two procedures: one is the representation method of super factors, and the other is the definition of division fitness function.

### 3.5.1 Representation of hyperparameters

For LS- SVM, since the kernel function selected in this paper is RBF kernel function, there are two hyperparameters to be optimized, namely regularization factor $C$ and intra kernel factor $\sigma$. When PSO is used for optimization, each division is required to characterize the possible explanation of the optimization issue, that is, the combination of super factors. Therefore, in the optimization process of LS SVM, a two-dimensional vector is used to represent the combination of the two super factors $C$ and $\sigma$, that is, the position of the $i^{th}$ division can be expressed as Equation 8.

$$X_i = (C_i, \sigma_i) \tag{8}$$

### 3.5.2 Fitness function

Fitness is a measure to evaluate the position of divisions, and also indirectly describes the generalization performance of LS SVM design. In this paper, the mean square error (MSE) of the prediction results is selected as the performance index of the prediction design, and its mathematical definition is presented in Equation 9.

$$f = \frac{1}{n}\sum_{j=1}^{n}\left(y_j - \hat{y}_j\right)^2 \tag{9}$$

Where $y_j$ represents the actual output value of the $j^{th}$ sample; $\hat{y}_j$ represents the predicted value of its design. By kernel function expression is presented in Equation 10.

$$K(x_i, x_j) = \exp\left(-\frac{|x_i - x_j|}{\sigma^2}\right) \tag{10}$$

And LS- SVM regression expression is shown in Equation 11.

$$f(x) = \sum_{i=1}^{n} a_i K(x_i \cdot x_j) + b \tag{11}$$

It can be seen that $f$ can be regarded as the composite function of $C$ and $\sigma$. In the fitness evaluation, the smaller the error, the better the division position. Then the optimization problem can be described as Equation 12 and 13.

$$\min_{C,\sigma} f = \frac{1}{n}\sum_{j=1}^{n}\left(y_j - \hat{y}_j\right)^2 \tag{12}$$

$$s.t. C \in [C_{\min}, C_{\max}], \sigma \in [\sigma_{\min}, \sigma_{\max}] \tag{13}$$

Where $C_{min}$, $C_{max}$ and $\sigma_{min}$, $\sigma_{max}$ represent the minimum and maximum values of $C$ and $\sigma$ respectively. In the designing process of LS-SVM, PSO is used to search in the value range of $C$ and $\sigma$ to minimize the fitness value $f$ of equations (12) and (13), then the solution vector $(C, \sigma)$ is the optimal super factor to be found by LS-SVM.

## 3.6 Construction cost prediction process based on PSO – LSSVM

The following designing concepts may be created using the basic study on PSO procedure and LSSVM design mentioned above:

i. The preprocessed historical statistics are formed into an example matrix by sample clustering and index dimensionality reduction.

ii. The exercise data set and the estimate data set should be mentioned.

iii. Define the factors range of standards $C$ and $\sigma$, and initialize the populationn $X = \{X_1, X_2, \ldots, X_m\}$ composed of $M$ divisions by using PSO procedure, where $X_i = \{C_i, \sigma_i\}$.

iv. It calculates and contrasts the division fitness with the training data set, the specific optimum assessment $P_{best}(i)$ and the global optimum assessment Grest are regular, and the speed and location of every division are efficient.

*v.* Iterate repeatedly until the end conditions are met (minimum fitness value).

*vi.* Output optimization hyperparameters $C$ and $\sigma$ and assigned to LS SVM prediction design.

*vii.* Train the design with the training regular, input the prediction sample data to predict the design, and achieve the optimum result.

In this manner, based on the actions above and combined with the actual engineering situation, the factors of PSO procedure can be set applicably, and the construction on the basis of factor optimization, project cost projection is possible.

Table 1: Input set of prediction design

| **Category** | **Sample Number** | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Type 1** | 19 | 17 | 3 | 49 | 21 | 32 | 16 | 39 | 11 | 18 | 12 | 38 | 35 | 34 | 14 | 2 | 40 |
| | 5 | 29 | 25 | 46 | 42 | 1 | 36 | 31 | 41 | 13 | 30 | 45 | 23 | 50 | 37 | 7 | |
| **Type 2** | 4 | 20 | 9 | 43 | 26 | 28 | 47 | 10 | 44 | 33 | 27 | 22 | 6 | 48 | 8 | 24 | 15 |

Table 2: Clustering results of sample system

| **Sample Number** | **Principal Component** 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| 1 | 0.169 | -1.011 | 0.482 | 0.803 | -1.248 | -0.555 | -0.542 | -0.002 |
| 2 | -1.568 | -0.474 | 0387 | -0.328 | 1.490 | -1.002 | 1.131 | -0963 |
| 3 | -0.393 | 2.296 | -1.077 | 0.042 | -0.010 | -1.360 | 0.137 | -2.062 |
| 4 | 0.678 | -0.675 | -1.247 | 0.569 | 0.615 | -1.633 | 0.1 08 | 0.821 |
| 5 | 1.644 | 0.570 | 1.315 | -0.252 | 0.471 | -1.446 | 0.504 | -0.717 |
| 6 | -0.697 | 0.076 | -1.547 | -0.215 | 0.414 | -0.419 | -0.085 | 0.102 |
| 7 | -0.790 | -1.428 | -1.585 | 0.557 | 0.460 | 0.380 | 0.680 | 0.779 |
| 8 | 0.555 | 0.071 | -0.269 | 0.939 | -0.118 | 1.159 | 1.321 | 0.531 |
| 9 | -1.797 | -0.133 | 2.009 | 0.314 | 0.441 | 0.012 | -1 .001 | -0.956 |
| 10 | -0.404 | 0.688 | -0.726 | -1.090 | -0.182 | -0.449 | -0. 354 | 0.417 |
| 11 | -0.107 | 2.031 | -1.089 | 0.085 | -1.111 | 0. 664 | -0.434 | 0.143 |
| 12 | -0.720 | -0.855 | 0.180 | 0.217 | -0.515 | 0.923 | -1 026 | 1.248 |
| 13 | -0.810 | 1.252 | 0.573 | 1.467 | -0.019 | 2.743 | -0.399 | -0.269 |
| 14 | -0.021 | 1.638 | 0.816 | -1.529 | 2.195 | 1.140 | -1.385 | 0.449 |
| 15 | 1.075 | 0.444 | 0.912 | 0.611 | -0.307 | -0.963 | -2.072 | 1.034 |
| 16 | 1.252 | -0.810 | -1.135 | -0.155 | -0.343 | -0.061 | -0.430 | -1 .043 |
| 17 | 0.489 | 0.162 | -0.924 | -0.964 | -0.478 | 0.534 | 0.858 | -1.807 |
| 18 | 0.465 | 0.382 | 0.687 | 1.744 | -0.282 | -0.494 | -0.183 | 0.794 |
| 19 | -0.301 | -1.664 | 1.444 | -1.663 | 1.404 | 0.239 | 2.188 | -0.142 |
| 20 | -0.112 | 0.870 | -0.741 | -1.858 | -0.516 | 1.214 | -1.910 | 0.598 |
| 21 | -1.709 | 0.021 | -1.006 | 0.790 | 1.044 | 0.119 | -0.683 | 1.244 |
| 22 | -1. 094 | 0.056 | 1.408 | -0.499. | -1.306 | -1.438 | -0.908 | 0.342 |
| 23 | 0.796 | -0.723 | 0.182 | -0.731 | 1.395 | 0 989 | -0.906 | -0.193 |
| 24 | 1.976 | 0.103 | -0.439 | 0.096 | 0.825 | -0. 994 | 0.204 | 0.950 |
| 25 | -0.568 | 0.240 | 1.076 | -0.724 | -1 .700 | -0.789 | 0.733 | -1.348 |
| 26 | -1.387 | -0.409 | -0.862 | 0.912 | -0.697 | -0.238 | 0.245 | -0.918 |
| 27 | 0.290 | -0.957 | -1.378 | -1.294 | -0.297 | -0.034 | 0.939 | 0.205 |
| 28 | 0.355 | 0.090 | 0.191 | 2. 665 | 1.338 | -0.277 | -0.092 | -0.529 |
| 29 | 0.073 | -1.748 | -0.123 | -0.782 | -0.556 | 0.082 | 0.384 | 0.037 |
| 30 | 0.541 | 0.517 | 1.336 | -0.520 | -2.183 | 0.395 | 1.466 | 2.204 |
| 31 | -0.180 | -1.448 | 0.500 | 0.590 | -0.606 | 0.706 | 1.679 | -0.658 |
| 32 | -0.049 | 1.137 | 0.217 | -0.295 | 1.344 | -0.847 | 0.518 | 1.345 |
| 33 | 2.350 | -0.310 | 0.432 | 0.498 | -0.133 | 1.699 | 0.680 | -1.635 |

## 3.7 Model implementation environment

MATLAB (Matrix Laboratory) is a scientific computing environment for mathematical calculation, programming development and result visualization. It integrates the functions of matrix operation, numerical analysis, design establishment and simulation into a convenient visual window, which provides convenience for the solution of many research problems. Different from C language, FORTRAN and other computer programming languages, Matlab can interactively accept various instructions from users to output results, and has developed many toolboxes for specific problems, which is convenient for users to directly learn and apply the corresponding methods. Therefore, this study chooses this platform to complete the extremely complex operation process in PSO - LSSVM prediction design.

### 3.8 Data processing

The data collected in this paper comes from a reconstruction construction project. This paper systematically clusters the sample data with the help of spss20.0 to obtain similar engineering classes. After 6 times of clustering, all cases can be combined into one category. In the last iteration process, all sample projects can be divided into two categories, including 33 in the first category and 17 in the second category, as shown in Table 1. In order to overcome the error caused by too small sample size and make the prediction design achieve better prediction effect, the first type of similar samples with large sample size are selected for further prediction analysis. The input data set of the prediction design can be obtained according to the attribute value of the sample, as shown in Table 2.

## 4 Results and analysis

The example matrix states that the main 25 of the 33 matters are utilized as training examples for knowledge and preparation, and the trained design is used to test the remaining eight collections of data. To more effectively assess how the design applies to project cost prediction following factor optimization, three methods of BP-NN, LS- SVM and PSO- LSSVM stay selected for project cost simulation prediction.

### 4.1 BP-NN design simulation and prediction

To finish the construction of the method, the BP-NN software of MATLAB must be used to forecast and analyze engineering sample data. To construct a new BP-NN net, first call the factor setting function new FF. Next, call the train task to train the BP neural network using the training set of data. The maximum number of iterations is 1000, the knowledge feature is 0.05, and the motion feature is 0.65 all at the same time. Finally, predictions are made using the SIM task and the qualified NN. Figure 2 depicts the relationship between the test sample's actual value and the expected cost value.

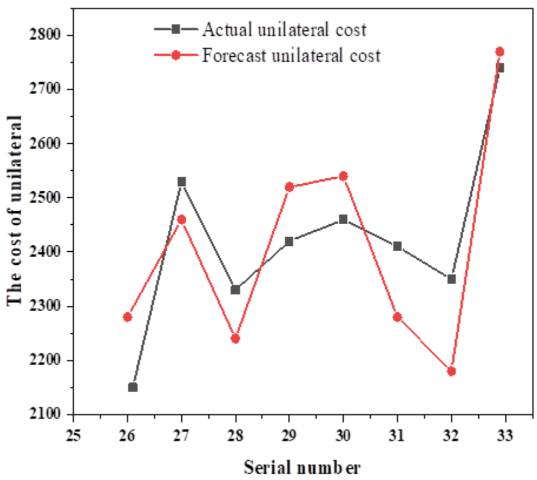



Figure 2: Prediction curve of BP-NN design.

### 4.2 LS- SVM model simulation prediction

The standard LS-SVM design is established to train and predict the sample data, and the standardized program is compiled under the environment of matlab2016a. The super factor C = 10 is determined by trial-and-error method, σ= 30. The design is created and trained using the trainlssvm function, examination examples are introduced into the trained design, prediction is made using simlssvm, and visualization is done using the plot LSSVM task. The cost prediction findings are displayed in Figure 3.

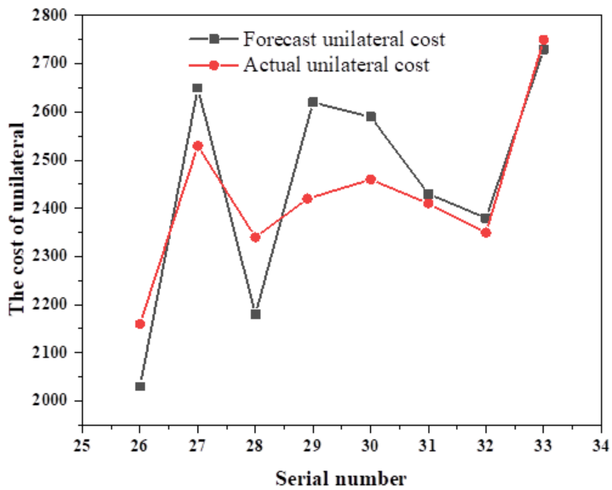



Figure 3: Prediction curve of LS-SVM design.

### 4.3 PSOLSSVM model simulation prediction

In order to analyze cost prediction, the PSOLSSVM design is utilized. A transfer into the libsvm-3.22 toolbox is the underlying assumption, and research on factor situation in the prediction design is incorporated, the super factor's value range of $C$ and $\sigma$ is set to [0, 100]. In parallel, the PSO procedure's factors are set to population size pop = 20; Evolution times Max Gen = 200; Inertia weight feature $\omega = 0.5$; Knowledge factor $c_1 = c_2 = 2$. By applying the radial basis task (kernel = rbf_kernel ') and using the mean square deviation of the predicted value of the examination set as the fitness value, the PSO-LSSVM prediction design is created. The value of the optimized factor is: $C$ = 13.5201, $\sigma$ = 46.4981. Figure 4 displays the test samples' findings for cost prediction.

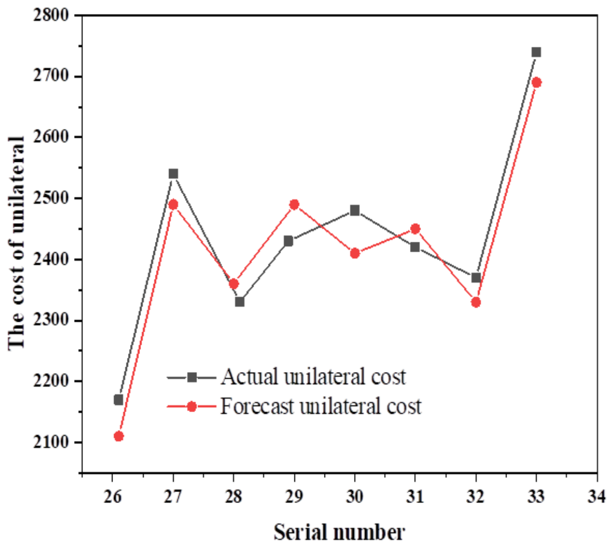



Figure 4: PSO-LSSVM design's prediction curve.

Table 3: Comparison of prediction results of different procedures

| Test sample | Actual value of unilateral cost | Predicted value of unilateral cost | | |
|---|---|---|---|---|
| | | BP neural network | LS-SVM | PSO-LSSVM |
| 26 | 2151.23 | 2274.39 | 2042. 03 | 2097.26 |
| 27 | 2537.89 | 2463.72 | 2648. 10 | 2487.52 |
| 28 | 2329.96 | 2235.11 | 2188.04 | 2352.86 |
| 29 | 2422.11 | 2519.03 | 2616.97 | 2486. 13 |
| 30 | 2465.89 | 2548. 85 | 2592. 15 | 2411.71 |
| 31 | 2418.21 | 2281. 60 | 2436. 50 | 2442. 57 |
| 32 | 2356.91 | 2183.29 | 2382. 28 | 2329.18 |
| 33 | 2749.11 | 2772.78 | 2721.72 | 2696.45 |

Table 4: Error in the test sample's expected value compared to its actual value

| Test sample | Relative error | | | Relative error of mean absolute value | | |
|---|---|---|---|---|---|---|
| | BP neural network | LS-SVM | PSO-LSSVM | BP neural network | LS-SVM | PSO-LSSVM |
| **26** | -5.61 | 5.17 | 2.49 | 4.23 | 3.94 | 1.82 |
| **27** | 2.81 | -4.43 | 1.87 | | | |
| **28** | 4.10 | 6.17 | -0.87 | | | |
| **29** | -4.12 | -8.12 | -2.56 | | | |
| **30** | -3.45 | -5.21 | 2.19 | | | |
| **31** | 5.74 | -0.67 | -1.10 | | | |
| **32** | -7.46 | -1.16 | 1.21 | | | |
| **33** | -0.79 | 1.21 | 1.89 | | | |

## 4.4 Analysis of prediction results

Table 3 displays a comparison of the outcomes of the above methodologies calculations. As indicated in Table 4, the relative fault δ and regular total percentage error are used to demonstrate the influence of various procedures on the prediction result of the design.

$$\delta = \frac{y_i - \hat{y}_i}{y_i} \tag{13}$$

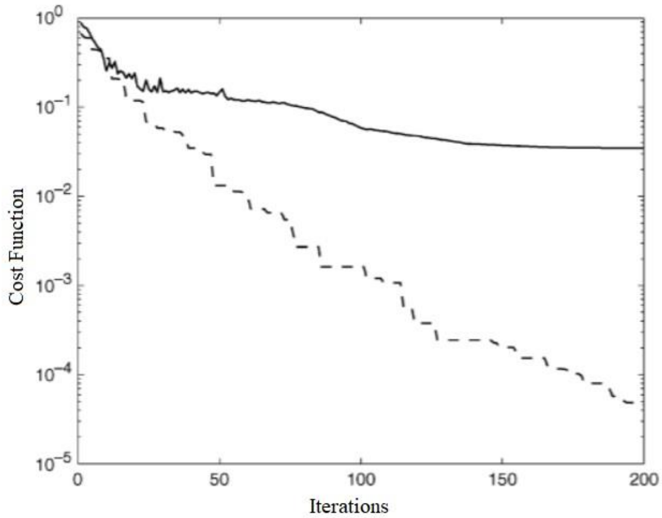
$$MAPE = \frac{1}{N}\sum_{i=1}^{n}|\delta| \times 100\% \tag{14}$$

Where $y_i$ and $\hat{y}_i$ indicate the cost's projected and actual values, respectively of the $i^{th}$ sample, and N is the number of test samples.

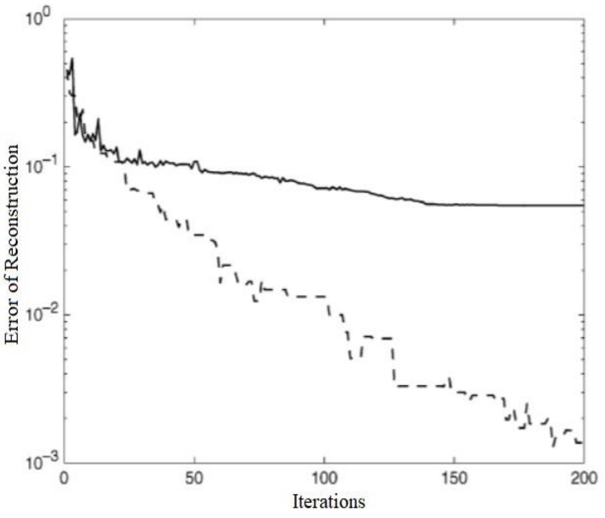
### 4.4.1 Accuracy analysis

By looking at the data in Table 4, it can be seen that the design performs well and can encounter the precision necessities of production project cost prediction in the early stages of production. The relative errors of LS-SVM, PSO-LSSVM, and BP neural network-based building project cost prediction are controlled within + 10%.

The optimized LS-SVM design significantly lowers the regular complete value relative fault whereas the BP-NN average absolute value relative error is nearly identical to that of the regular LS-SVM design. Consequently, the PSO-LSSVM-based production price prediction design performs superior in error management and has improved prediction precision.




(a)




(b)

Figure 5: (a) Cost task, (b) error of reconstruction with respect to the number of iterations

The accuracy of the proposed procedure is estimated with respect to the cost task and error of reconstruction. The observation of cost task and error of reconstruction with respect to the number of iterations for the proposed procedure is depicted in Figure 5. It is observed from the experimentation that the proposed procedure outperforms for both cost task and error of reconstruction in comparison with existing baseline design [5, 6].

#### 4.4.2 Stability analysis

Table 4 shows that the projected comparative fault dissemination interval using the BP-NN design is [-7.46%, 5.74%], with a range of 13.12%.The range of the comparative fault dissemination interval predicted using the LS SVM design is 14.22%, and it is between [-8.12%, 6.17%]. According to the PSO-LSSVM design, the relative error dissemination interval is [-2.56%, 2.49%], and its range is 5.21%. It is clear that the PSO procedure-optimized prediction design outperforms the LS-SVM design in terms of prediction stability and robustness of the prediction effect.

#### 4.4.3 Forecast time analysis

The prediction period based on the BP-NN design is 9.15 seconds from the start of the programme running to creating the prediction graphic. According to the LS-SVM design, the forecast time is 3.17 seconds, whereas the PSO-LSSVM design predicts the time to be 13.14 seconds. The PSO procedure's optimization increases the design's training time, but the time difference between the three has minimal bearing on how much building projects will ultimately cost in real life.

## 5 Conclusions

In this paper, the research on dynamic cost estimation of reconstruction project based on particle swarm optimization procedure is proposed. MATLAB platform is used to design simulation and analysis from data collection to preprocessing. The project cost prediction design system based on factor optimization is applied to practical engineering cases, which realizes the good combination of theory and practice. The experimental results verify the efficiency and accuracy of the prediction design based on PSO optimized LS-SVM. Numerical results show that proposed procedure leads to better reconstruction compared to existing design with same number of iterations. Although, both procedures are consistent and deliver accurate reconstruction shape even when the scattered field dimensions are despoiled by additive white Gaussian noise. For different construction projects, how to form a more scientific and perfect construction project cost prediction index system, or establish an index system platform to select and change indicators according to different engineering projects needs further research.

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