Scientific Journal of Intelligent Systems Research Volume 4 Issue 6, 2022
ISSN: 2664-9640

Supply and Recycling Network Design for New Energy Vehicle Power Battery under Uncertainties

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Abstract

The automobile industry is an important industry supporting the development of China's national economy. New energy vehicles have developed rapidly in recent years with their advantages of energy conservation and emission reduction. However, a large number of power batteries are about to be scrapped. If they are not handled properly, they will cause serious environmental pollution and waste of resources. Therefore, this paper establishes a new energy vehicle power battery supply recycling network model with the goal of minimizing the total system cost and considering the constraints of multiple random scenarios and multiple network levels. Then, based on the characteristics of response surface model and particle swarm optimization algorithm, an improved particle swarm optimization algorithm based on response surface model is designed, and different scale examples are set to verify the algorithm. The results show that the improved particle swarm optimization algorithm based on response surface model has good efficiency and quality.

Keywords

New energy vehicle power battery; Uncertainty; Logistics network design; Particle swarm optimization algorithm; Response surface model.

1. Introduction

Automobile industry is an important industry supporting the development of China's national economy. Since the 21st century, the development of a new generation of energy-saving and environment-friendly vehicles represented by new energy electric vehicles has become a universal consensus all over the world. As the core component of new energy vehicles, the service life of power battery is generally 5-8 years. China's new energy vehicle power battery is about to usher in a centralized scrapping period. Although new energy vehicles are relatively green and environment-friendly, there are still heavy metals such as nickel, cobalt, manganese and other organic pollutants in the electrolyte of new energy vehicle power battery. If not handled properly, it will cause serious harm to human body and environment and cause huge waste of resources. In addition, after scrapping, the power battery still has a high voltage ranging from 300-1000v. If it is operated improperly in the process of recovery, disassembly and treatment, it may cause explosion. Therefore, it has become a major concern in the development of new energy vehicles to do a good job in the recycling and scrapping of waste batteries and avoid "secondary pollution" and resource waste of power batteries.

In this paper, the power battery supply recovery process of new energy vehicles is described as a cost minimization problem under the premise of uncertain recovery quality. Aiming at the problems existing in the power battery supply recovery process of new energy vehicles, the regional library location model for determining the number and location of Regional Libraries and the cost minimization model under uncertain recovery quality of power batteries are successively established.

The organizational structure of the paper is as follows. The first section introduces the background of new energy vehicle power battery. The second section reviews the relevant technical literature from the perspectives of power battery recovery, uncertain demand and solution methods. In the third section, a new energy vehicle power battery supply recycling network is proposed, and the model of this problem is established. In order to solve the model, the fourth section proposes an algorithm based on traditional PSO by introducing RBF response surface model. Section 5 presents small-scale and large-scale numerical results based on a case study. The sixth section summarizes the whole thesis.

2. Literature References

2.1. Power Battery Recovery

At present, foreign scholars have carried out research on various problems related to power battery recycling, such as battery margin estimation, recycling mode, recycling channel, recycling network design and so on. Change L [1] proposed a method to quickly estimate the residual capacity of waste power batteries from the perspective of current distribution in parallel connection units. De Giovanni et al. [2] studied the game problem of two-stage closed-loop supply chain and concluded that the battery manufacturer occupies the residual value of waste power batteries. Natkun et al. [3] studied the recovery rate of different types of batteries, predicted the sales volume of new energy vehicles under the influence of different economic, social, ecological and technical factors, and analyzed the service life of different types of power batteries and the possible service life of batteries in recycling. Chuang et al. [4] studied the newsboy model with unstable demand and uncertain cost recovery. Tosarkani et al. [5] first applied the complete fuzzy programming method to the multi-objective power battery reverse logistics network, and solved the uncertain problem by combining fuzzy programming, stochastic programming and robust optimization.

2.2. Forward and Reverse Logistics Network

There is little research on forward logistics network at home and abroad. Most scholars study forward logistics network and reverse logistics network together. Ramezani et al. [6] established a stochastic multi-objective model for forward / reverse logistics network design in uncertain environment with the goal of maximizing profit, customer responsiveness and quality. Ashfari [7] et al. Established a robust model of forward and reverse integrated logistics network under uncertainty, and optimized the location and scale of facilities and service centers in forward / reverse logistics. Khatami et al. [8] redesigned the existing forward / reverse logistics network based on the uncertainty of product demand, established a random mixed integer model of multi cycle and multi product supply chain network, and used K-means clustering algorithm to reduce the number of scenarios for calculation.

In 1981, Lambert and stock first put forward the concept of reverse logistics, describing reverse logistics as "flow in the opposite direction of forward logistics". Sibel et al. [9] designed the reverse logistics network of German washing machines and drum dryers, established a profit maximization model considering single-stage and multi-stage, and solved the location of detection center and re-manufacturing center. Shokouhyar et al. [10] established a two-stage reverse logistics network planning model for waste electrical and electronic equipment based on the goal of sustainable development, and designed a multi-objective genetic algorithm to determine the best location of the collection center and recycling place.

2.3. Solving Algorithm

For the optimization design of logistics network, the current algorithms are mainly divided into accurate algorithm and heuristic algorithm. Yuzhuo Qi [11] established a mixed integer programming model for the production path problem of reverse logistics and remanufacturing, which was solved by branch cutting guided search algorithm. cHao et al. [12] proposed a dynamic programming algorithm to solve the optimal combination strategy of transportation modes in container multimodal transport system. Schweiger et al. [13] used the hybrid tabu search algorithm to solve the optimization problem of paper recycling network, so as to realize the location decision of continuous and discrete facilities. Sze et al. [14] designed an adaptive variable neighborhood search algorithm using large neighborhood search algorithm as diversification strategy for the path problem with Limited vehicle capacity.

2.4. Summary of Literature Review

Because the power supply recovery network of new energy vehicles designed in this paper has a large scale, involves many network levels and nodes, and considers the influence of multiple uncertain random factors, it is difficult to solve it by accurate algorithm. Therefore, this paper adopts particle swarm optimization algorithm and improves it according to its characteristics combined with response surface model, and designs an improved particle swarm optimization algorithm based on response surface model to solve large-scale network problems.

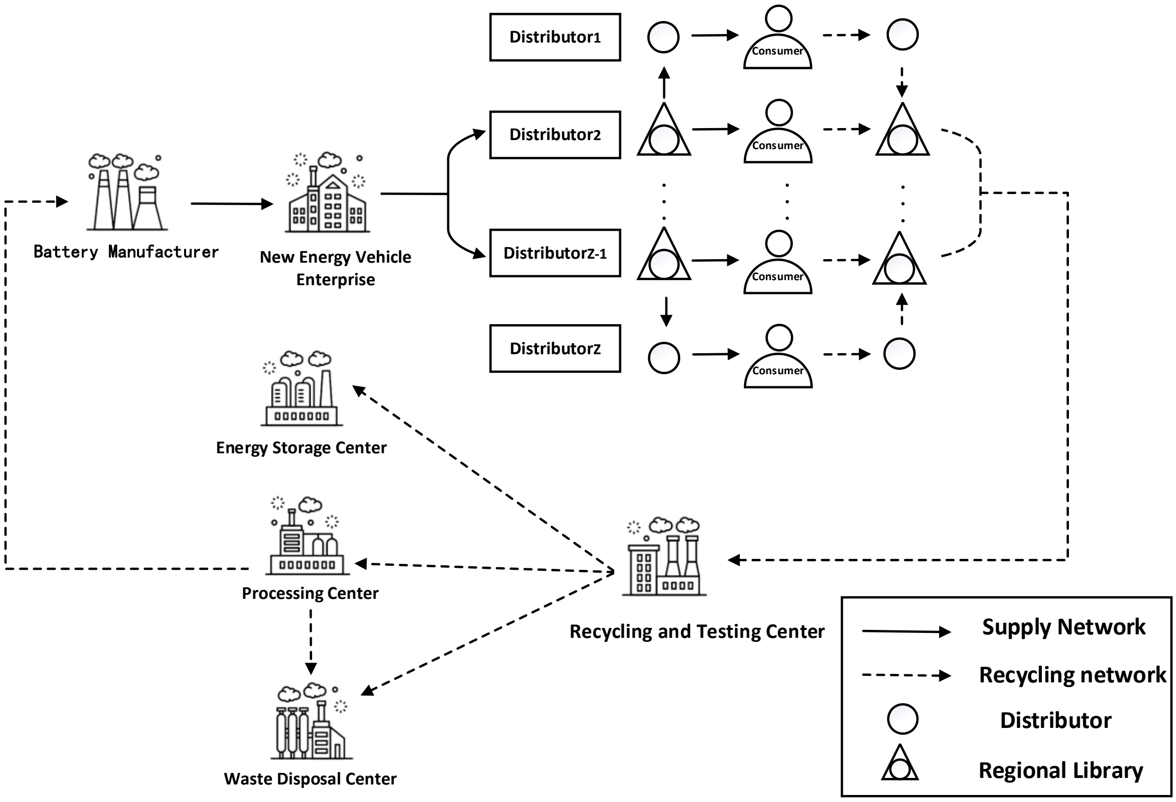

Figure 1: Design Diagram of Power Battery Supply Recycling Network of New Energy Vehicles

3. Establishment of power battery supply and recovery network model

3.1. Problem description

This paper studies the optimal design of the power battery supply recovery network of new energy vehicles. Based on the characteristics of the supply and recovery network, this chapter applies some nodes in the supply network to the recovery network to reasonably design the power battery supply recovery network of new energy vehicles, so as to reduce the total cost of the system.

In addition, the design considers the advantages of integrating different power battery recycling modes: the regional library selected by dealers in the supply network is used as the power battery recycling point to improve the recycling efficiency of power batteries; Make use

ISSN: 2664-9640

of the transportation advantages and logistics network advantages of third-party logistics enterprises to improve the circulation efficiency of power batteries; It is decided to establish professional power battery processing nodes such as recycling detection center, processing center and energy storage center to improve the echelon utilization rate of power battery and realize the effective recycling of power battery. The specific chain recycling network is shown in Figure 1.

3.2. Model Assumptions

The optimization design of power battery supply recycling network for new energy vehicles is complex, and it is difficult to take all the factors involved into account. Therefore, the assumptions of this paper mainly include the following points:

(1) In terms of cost, only recovery cost, construction cost, transportation cost and operation cost are considered, and the fixed cost of each facility is known. The unit recovery cost of battery in the same scenario is the same.

(2) The unit transportation cost of each facility node is the same. The freight of products from dealers to consumers and Regional Libraries, and the freight of products from Regional Libraries and consumers to dealers are not included in the model.

(3) Battery manufacturers, new energy vehicle manufacturers, dealers and regional libraries exist in themselves, do not need to be rebuilt, and their operating costs are fixed.

(4) Battery manufacturers, new energy vehicle manufacturers, regional warehouses, recycling and testing centers, treatment centers, waste disposal centers and energy storage centers have the maximum receiving and processing capacity.

(5) According to the demand of the consumer group, the probability of the recycling detection center transporting to other functional nodes and the processing center transporting to other functional nodes is random and follows the normal distribution. The above probabilities are not set differently for a single node within the same level.

(6) The model is constructed based on the single cycle situation.

3.3. Symbol definition

S :Collection of random scene, $S=\{1,2,\ldots s,\ldots,|S|\}$

G :Collection of battery manufacturers, $G=\{1,2,\ldots g,\ldots,|G|\}$

H :Collection of new energy vehicle manufacturers, $H=\{1,2,\ldots h,\ldots,|H|\}$

T :Consumer group collection, $T=\{1,2,\ldots t,\ldots,|T|\}$

I :Area library collection, $I=\{1,2,\ldots i,\ldots,|I|\}$

J :Collection of recycling detection centers, $J=\{1,2,\ldots j,\ldots,|J|\}$

K :Collection of processing centers, $K=\{1,2,\ldots k,\ldots,|K|\}$

L :Collection of waste disposal centers, $L=\{1,2,\ldots l,\ldots,|L|\}$

M :Collection of energy storage centers , $M=\{1,2,\ldots m,\ldots,|M|\}$

3.4. Parameter definition

x_{ts} :Demand of consumer group T under scenario s

p_0 :Recovery cost per unit of power battery

N_g :Production capacity of battery manufacturer

N_h :Manufacturing capacity of new energy vehicle manufacturing enterprises

N_i :Storage capacity of Regional Library

N_j :Recycling detection capability of recycling Detection Center

N_k :Processing capacity of processing center

N_l :Processing capacity of waste disposal center

N_m :Storage capacity of energy storage center

ρ_s :Probability of scenario occurrence

θ_s :Recovery rate of power battery

α_{jks} :The probability that the power battery will be transported to the treatment center through the recycling and testing center

α_{jls} :The probability that the power battery will be transported to the waste disposal center through the recycling and testing center

α_{jms} :The probability that the power battery is transported to the energy storage center through the recycling and testing center

β_{kls} :The probability that the power battery will be transported to the waste disposal center through the processing center

β_{kgs} :The probability that the power battery will be re-manufactured by the processing center and transported to the battery manufacturer

c_{gh} : Unit transportation cost from battery manufacturer to new energy vehicle manufacturer

c_{hi} :Unit transportation cost of new energy vehicle manufacturing enterprises to regional warehouses

c_{ij} :Unit transportation cost from regional library to recycling Detection Center

c_{jk} :Recover the unit transportation cost from the detection center to the processing center

c_{jl} :Unit transportation cost from recycling detection center to waste disposal center

c_{jm} :Recover the unit transportation cost from the detection center to the energy storage center

c_{kl} :Unit transportation cost from treatment center to waste disposal center

c_{kg} :Unit transportation cost from processing center to battery production plant

d_{gh} :Distance from battery manufacturer to new energy vehicle manufacturing enterprise

d_{hi} :Distance from new energy vehicle manufacturing enterprises to Regional Libraries

d_{ij} :Distance from area library to recycling Detection Center

d_{jk} :Distance from recycling detection center to processing center

d_{jl} :Distance from recycling detection center to waste disposal center

d_{jm} :Distance from recovery detection center to energy storage center

d_{kl} :Distance from disposal center to waste disposal center

d_{kg} :Distance from processing center to battery factory

b_j :Recover the construction cost of the testing center

b_k :Construction cost of treatment center

b_l :Construction cost of waste disposal center

b_m :Construction cost of energy storage center

f_g :Operating cost of battery manufacturer

f_h :Operating cost of new energy vehicle manufacturing enterprises

f_i :Operating cost of Regional Library

f_j :Recover the unit product operation cost of the testing center

f_k :Unit product operation cost of processing center

f_l :Unit product operation cost of waste disposal center

f_m :Unit product operation cost of energy storage center

3.5. Definition of decision variables

x_{gs} :Original output of battery manufacturer g in scenario s

x_{ghs} :The number of power batteries transported from battery manufacturer g to new energy vehicle manufacturer h in scenario s

x_{his} :The Number of products delivered to regional warehouse I by new energy vehicle manufacturing enterprise h under scenario s

x_{its} :The number of power batteries transported from area library I to consumer t in scenario s

x_{tis} :The number of power batteries transported by consumer t to regional library I in scenario s

x_{ijs} :The number of power batteries transported from area library I to recycling detection center J under scenario s

x_{jks} :The number of power batteries transported from detection center J to processing center K in scenario s

x_{jls} :The number of power batteries transported from the recycling detection center J to the waste disposal center L in scenario s

x_{jms} :The number of power batteries transported from recovery detection center J to energy storage center m in scenario s

x_{kls} :The number of products transported from treatment center K to waste treatment center L in scenario s

x_{kgs} :The number of products transported from processing center K to battery manufacturer g in scenario s

Y_j :Whether the recovery detection center J is established. If it is established, the value is 1; otherwise, it is 0

Y_k :Whether the processing center K is established. If it is established, the value is 1; otherwise, it is 0

Y_l :Whether the waste disposal center L is established. If it is established, the value is 1; otherwise, it is 0

Y_m :Whether the energy storage center m is established. If it is established, the value is 1; otherwise, it is 0

ISSN: 2664-9640

3.6. Model Building

Total objective function = recovery cost + construction cost + transportation cost + operation cost

$$\min TC = TC_1 + TC_2 + TC_3 + TC_4 \tag{1}$$

$$TC_1 = \rho_s \sum_s \sum_t \sum_i x_{ti} p_0 \tag{2}$$

$$TC_2 = \sum_j Y_j b_j + \sum_k Y_k b_k + \sum_l Y_l b_l + \sum_m Y_m b_m \tag{3}$$

$$\begin{aligned} TC_3 = \rho_s \sum_s (&\sum_g \sum_h c_{gh} d_{gh} x_{ghs} + \sum_h \sum_i c_{hi} d_{hi} x_{his} \\ &+ \sum_i \sum_j c_{ij} d_{ij} x_{ijs} + \sum_j \sum_k c_{jk} d_{jk} x_{jks} + \sum_j \sum_l c_{jl} d_{jl} x_{jls} \\ &+ \sum_j \sum_m c_{jm} d_{jm} x_{jms} + \sum_k \sum_l c_{kl} d_{kl} x_{kls} + \sum_k \sum_g c_{kg} d_{kg} x_{kgs}) \end{aligned} \tag{4}$$

$$\begin{aligned} TC_4 = \rho_s \sum_s (&\sum_i \sum_j x_{ijs} f_j + \sum_j \sum_k x_{jks} f_k \\ &+ \sum_j \sum_l x_{jls} f_l + \sum_k \sum_l x_{kls} f_l + \sum_j \sum_m x_{jms} f_m) \end{aligned} \tag{5}$$

St.

$$x_{gs} + \sum_k x_{kgs} = \sum_h x_{ghs} \quad \forall g, \forall s \tag{6}$$

$$\sum_g x_{ghs} = \sum_i x_{his} \quad \forall h, \forall s \tag{7}$$

$$\sum_h x_{his} = \sum_t x_{its} \quad \forall i, \forall s \tag{8}$$

$$\sum_i x_{its} = x_{ts} \quad \forall t, \forall s \tag{9}$$

$$\theta_s \sum_i x_{its} - \frac{1}{2} \le \sum_i x_{tis} \le \frac{1}{2} + \theta_s \sum_i x_{its} \quad \forall t, \forall s \tag{10}$$

$$\sum_t x_{tis} = \sum_j x_{ijs} \quad \forall i, \forall s \tag{11}$$

$$\alpha_{jks} \sum_i x_{ijs} - \frac{1}{2} \le \sum_k x_{jks} \le \frac{1}{2} + \alpha_{jks} \sum_i x_{ijs} \quad \forall j, \forall s \tag{12}$$

$$\alpha_{jls} \sum_i x_{ijs} - \frac{1}{2} \le \sum_l x_{jls} \le \frac{1}{2} + \alpha_{jls} \sum_i x_{ijs} \quad \forall j, \forall s \tag{13}$$

$$\alpha_{jms} \sum_i x_{ijs} - \frac{1}{2} \le \sum_m x_{jms} \le \frac{1}{2} + \alpha_{jms} \sum_i x_{ijs} \quad \forall j, \forall s \tag{14}$$

$$\beta_{kls} \sum_j x_{jks} - \frac{1}{2} \le \sum_l x_{kls} \le \frac{1}{2} + \beta_{kls} \sum_j x_{jks} \quad \forall k, \forall s \tag{15}$$

$$\beta_{kgs} \sum_j x_{jks} - \frac{1}{2} \le \sum_g x_{kgs} \le \frac{1}{2} + \beta_{kgs} \sum_j x_{jks} \quad \forall k, \forall s \tag{16}$$

$$\sum_k x_{jks} + \sum_l x_{jls} + \sum_m x_{jms} = \sum_i x_{ijs} \quad \forall j, \forall s \tag{17}$$

$$\sum_l x_{kls} + \sum_g x_{kgs} = \sum_j x_{jks} \quad \forall k, \forall s \tag{18}$$

$$\sum_k x_{kgs} + x_{gs} \le N_g \quad \forall g, \forall s \tag{19}$$

$$\sum_g x_{ghs} \le N_h \quad \forall h, \forall s \tag{20}$$

$$\sum_h x_{his} \le N_i \quad \forall i, \forall s \tag{21}$$

$$\sum_t x_{tis} \le N_i \quad \forall i, \forall s \tag{22}$$

$$\sum_i x_{ijs} \leq Y_j N_j \quad \forall j, \forall s \tag{23}$$

$$\sum_j x_{jks} \leq Y_k N_k \quad \forall k, \forall s \tag{24}$$

$$\sum_j x_{jls} + \sum_k x_{kls} \leq Y_l N_l \quad \forall l, \forall s \tag{25}$$

$$\sum_j x_{jms} \leq Y_m N_m \quad \forall m, \forall s \tag{26}$$

$$\alpha_{jks} + \alpha_{jls} + \alpha_{jms} = 1 \quad \forall s \tag{27}$$

$$\beta_{kls} + \beta_{kgs} = 1 \quad \forall s \tag{28}$$

$$Y_j, Y_k, Y_l, Y_m \in (0,1) \quad \forall j, k, l, m \tag{29}$$

$$x_{gs}, x_{ghs}, x_{his}, x_{its}, x_{tis}, x_{ijs}, x_{jks}, x_{jls}, x_{jms}, x_{kls}, x_{kgs} \geq 0 \ \forall g, h, i, t, j, k, l, m, k, l, g, s \tag{30}$$

Aiming at the supply recovery network with uncertain power battery recovery quality of new energy vehicles, a mixed integer stochastic programming model aiming at minimizing the total system cost is established in this paper. Among them, the objective function (1) represents the minimization of four costs in the supply recovery network, including the recovery cost of power battery (2), the construction cost of recovery detection center, treatment center, waste material treatment center and energy storage center (3), the transportation cost between network nodes (4), and the operation cost of recovery detection center, treatment center, waste material treatment center and energy storage center (5).

Constraint (6) means that the power batteries recovered and originally manufactured by the battery manufacturer are transported to the whole vehicle manufacturing enterprise of new energy vehicles; Constraint (7) means that the power batteries received by the whole vehicle manufacturing enterprise of new energy vehicles are transported to the regional warehouse; Constraint (8) indicates that the new energy vehicles received by the regional library are transported to the consumer area; Constraint (9) indicates that the number of new energy vehicles transported from the regional library to the consumer group is equal to the demand of the consumer group; Constraint (10) means that all power batteries recovered from the consumer area are transported to the regional warehouse; Constraint (11) indicates that the power batteries recovered from the regional library are transported to the recovery and detection center; Constraints (12), (13) and (14) mean that the power batteries recovered by the recovery and detection center are transported to the treatment center, waste material treatment center and energy storage center respectively according to a certain probability after detection; Constraints (15) and (16) mean that the power batteries recovered by the treatment center are transported to the waste treatment center and the battery production plant respectively according to a certain probability after treatment; Constraints (17) and (18) represent the flow conservation of the recovery detection center and the treatment center respectively; Constraint (19) means that the sum of the received quantity and the original output of the battery manufacturer cannot exceed the upper limit of its capacity; Constraint (20) means that the receiving quantity of new energy vehicle manufacturing enterprises cannot exceed the upper limit of their capacity; Constraint (21) indicates that the receiving quantity of the area library cannot exceed its upper capacity limit; Constraint (22) indicates that the recycling quantity of the area library cannot exceed its upper capacity limit; Constraint (23) indicates that the recycling quantity of the recycling detection center cannot exceed its upper limit of capacity; Constraint (24) indicates that the recycling quantity of the processing center cannot exceed the upper limit of its capacity; Constraint (25) means that the recycling quantity of the waste treatment center cannot exceed its upper limit of capacity; Constraint (26) indicates that the recovery quantity of the energy storage center cannot exceed the upper limit of its capacity; Constraint (27) indicates that the sum of the probability of the number of power batteries transported to other areas detected by the recovery detection center is 1; Constraint (28) indicates that the sum of the product probabilities processed by the processing center and transported to other areas is 1; Constraint (29) specifies 0-1 variables; Constraint (30) indicates that the decision variable is nonnegative.

4. Proposed heuristic algorithm

Previous studies have fully proved the effectiveness of particle swarm optimization algorithm in solving the optimization design problem of power battery logistics network of new energy vehicles, while the agent model based on response surface is relatively less used in this problem. When particle swarm optimization algorithm is used to deal with high-dimensional complex problems, the algorithm may converge prematurely. Therefore, this paper considers the combination of response surface model and particle swarm optimization algorithm, and designs an improved particle swarm optimization algorithm based on response surface model to improve the efficiency and quality of problem solving in this paper. The advantages of RBF response surface model are: (1) nonlinear fitting and strong local approximation ability; (2) Good autonomous learning ability and fast learning convergence. Particle swarm optimization algorithm and RBF response surface model can complement each other. At the beginning, particle swarm optimization algorithm is used for global development, and then its iterative information and optimal solution information are used to build RBF response surface model. Then, under the information exchange mechanism set up in this paper, by applying RBF response surface model to particle swarm optimization algorithm, we can maintain the powerful global search ability of particle swarm optimization algorithm, and also have the characteristics of efficient convergence of radial RBF response surface model, which can avoid the algorithm falling into local optimization, so as to improve the solution efficiency and solution quality.

Therefore, the design idea is as follows Figure 2:

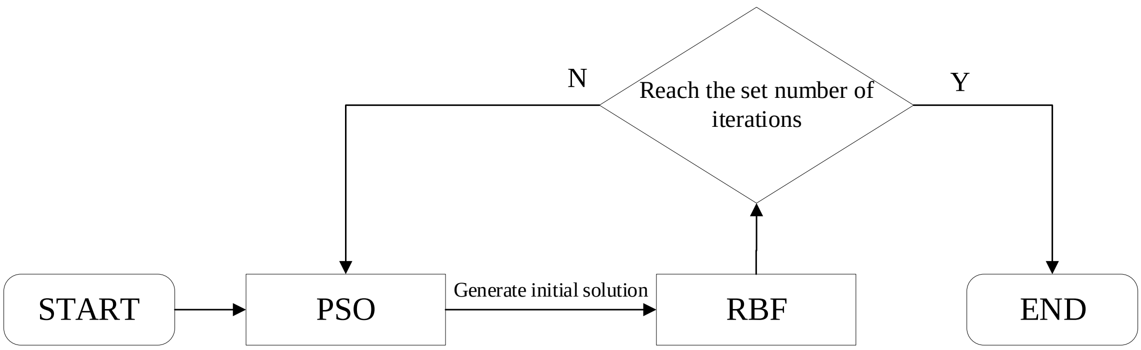

Figure 2: Improved particle swarm optimization process based on response surface model

Firstly, the standard particle swarm optimization algorithm is used to solve. When a certain number of iterations are met or the optimal solution is updated, certain rules are set according to the distance and fitness. M samples are selected from the initial sampling scheme samples and particle swarm optimization as the initial sample points of RBF. The distance evaluation adopts European distance: $d_i = \| (x_{im} - x_m *) \|$, where $x_m *$ is the optimal solution.

Then, according to the solution set of the input response surface model, that is, the sample points, the RBF model is constructed and solved iteratively. When the number of solutions based on the response surface model reaches the set optimal value or the number of updates of the current optimal solution reaches the set threshold, the sample points of the sample set are sorted from small to large according to their real evaluation value, and the first m sample outputs are taken as the population of particle swarm optimization algorithm. In addition to the termination principle shown in Figure 3, this paper also sets the overall maximum number of iterations, that is, the sum of the total number of iterations of particle swarm optimization algorithm and the number of iterations based on response surface model.

4.1. Encoding mode and decoding mode

In this paper, the decision variables for the construction of each alternative function node are coded in the form of direct coding, as shown in Figure 4.4. According to the fact that there are three recovery and detection centers, two energy storage centers, two treatment centers and two waste disposal centers, an array with a length of 3 + 2 + 2 + 2 is set, in which 1 represents the establishment of the alternative function node and 0 represents the abandonment of the alternative function node.

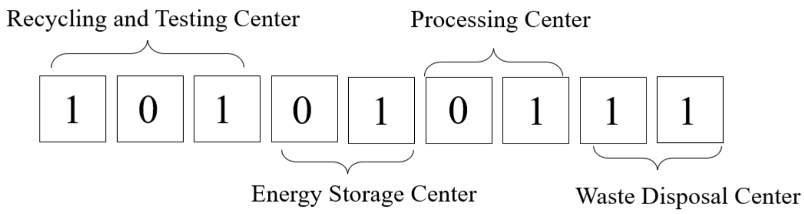

Figure 3: Example of Encoding Mode and Decoding Mode

The decoding form of this paper is shown in Figure 3. After assigning the 0-1 variable to each function node, when the first position of the recycling detection center array is 1, the processing capacity of the first recycling detection center is its original capacity, and when the second position of the recycling detection center array is 0, the processing capacity of the second recycling detection center is 0.

4.2. PSO Algorithm Design

When the improved particle swarm optimization algorithm based on RBF response surface model designed in this paper starts, first enter the particle swarm optimization part to generate the initial particles. Particle swarm optimization algorithm requires the randomness of particle positions, so that they can be dispersed in each position of the feasible region as much as possible. At the same time, considering the requirements of RBF for solution set, this paper forms N particles according to the initial sample generation scheme mentioned above.

After generating the initial particles, the fitness value of each particle is solved as the initial individual optimal value, and the particle with the best fitness is selected as the group optimal solution. Then, the particles are updated according to the formula and the iteration of the particle swarm part is carried out until the end of the algorithm of the particle swarm part.

The algorithm flow of particle swarm optimization designed in this paper is shown in Figure 4.

As shown in the figure above, the algorithm of particle swarm optimization first determines whether it is the initial operation or returned by the algorithm based on response surface model. If it is the initial operation, the initial particles will be generated. Otherwise, set the initial local optimal value of each particle as the current particle fitness, and then iterate the algorithm according to the process of particle swarm optimization algorithm. In the iterative process of particle swarm optimization algorithm, its optimization rules make the motion of particles not tend to the inferior solution, that is, the inferior solution particles do not have the function of guiding the direction of group motion. In this paper, the fitness of not calculating the inferior solution is set to speed up the operation speed. The inferior solution that is not worth calculating is considered from the perspective of network traffic balance. For example, if the demand of consumer groups is known, the maximum recovery can be approximately obtained. Then, according to the establishment of each center, preliminarily calculate whether the traffic balance is satisfied, that is, the total recovery of a certain type of function node should be less

ISSN: 2664-9640

than the superposition value of the upper bound of the processing capacity of all function nodes of this type. When such particles are generated, they are repaired. Firstly, randomly select e positions with value of 0 in the particle solution, assign these positions to 1, and then evaluate the inferior solution until the inferior solution meets the requirements. After the above steps, it not only ensures that the position of particles does not change, but also saves the occupation of computing resources and reduces the running time of the algorithm.

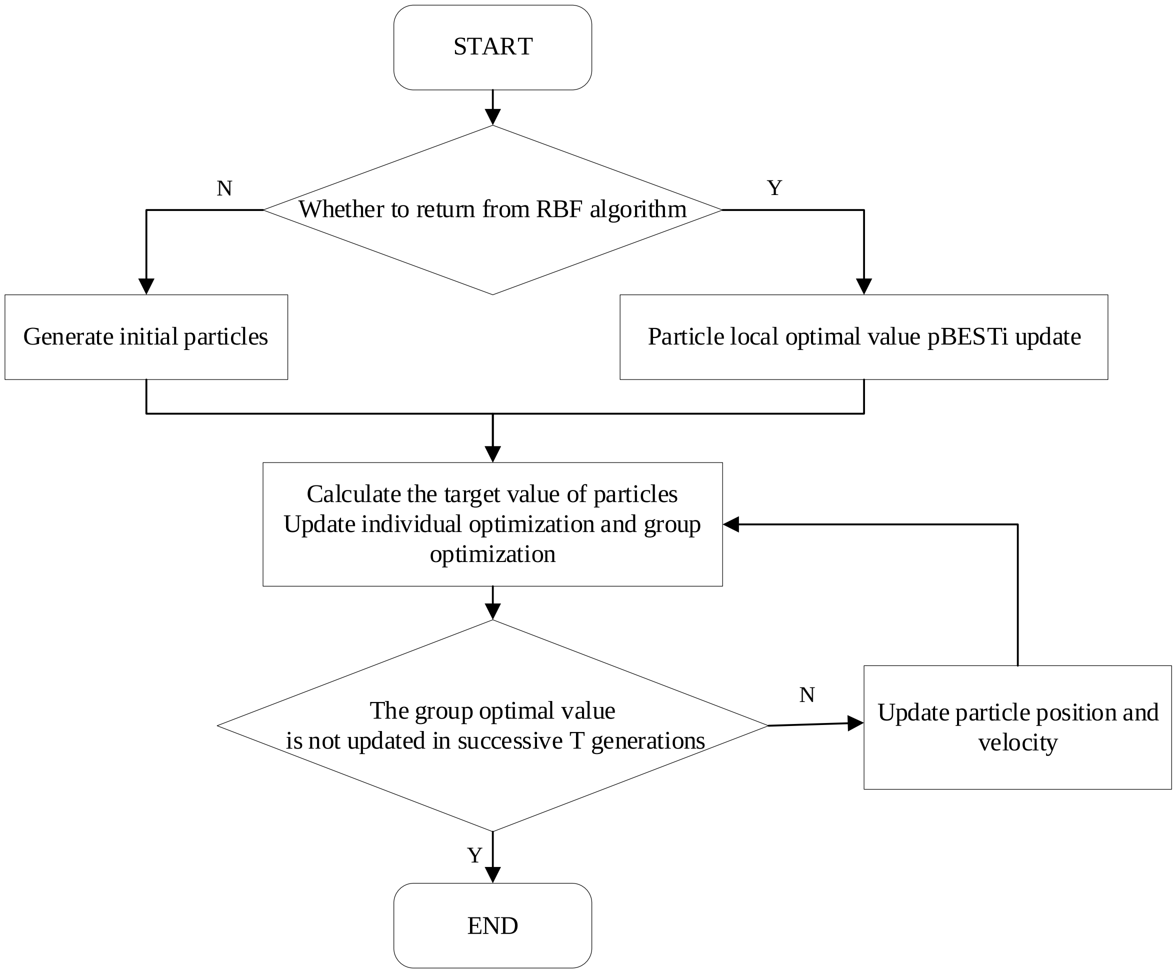

Figure 4: Algorithm flow of PSO

4.3. Algorithm design based on RBF response surface model

When the particle swarm optimization algorithm converges prematurely, the particle swarm optimization algorithm will generate an initial solution set as the data set of RBF response surface model, and then carry out iterative optimization according to the algorithm flow based on response surface model.

The iterative flow of the algorithm based on RBF response surface model designed in this paper is shown in Figure 5.

As shown in the figure above, the algorithm based on response surface model designed in this paper mainly includes five steps: constructing and generating RBF model, constructing candidate points, evaluating candidate points, updating the optimal solution and solution set, and updating the disturbance probability. The disturbance probability is a dynamic decimal, which is the main parameter of candidate point generation.

This paper considers two aspects to score the candidate points, one is the Euclidean distance between the candidate point and the current optimal solution point, and the other is the predictive evaluation value of RBF between the candidate node and the candidate node. The specific process is as follows:

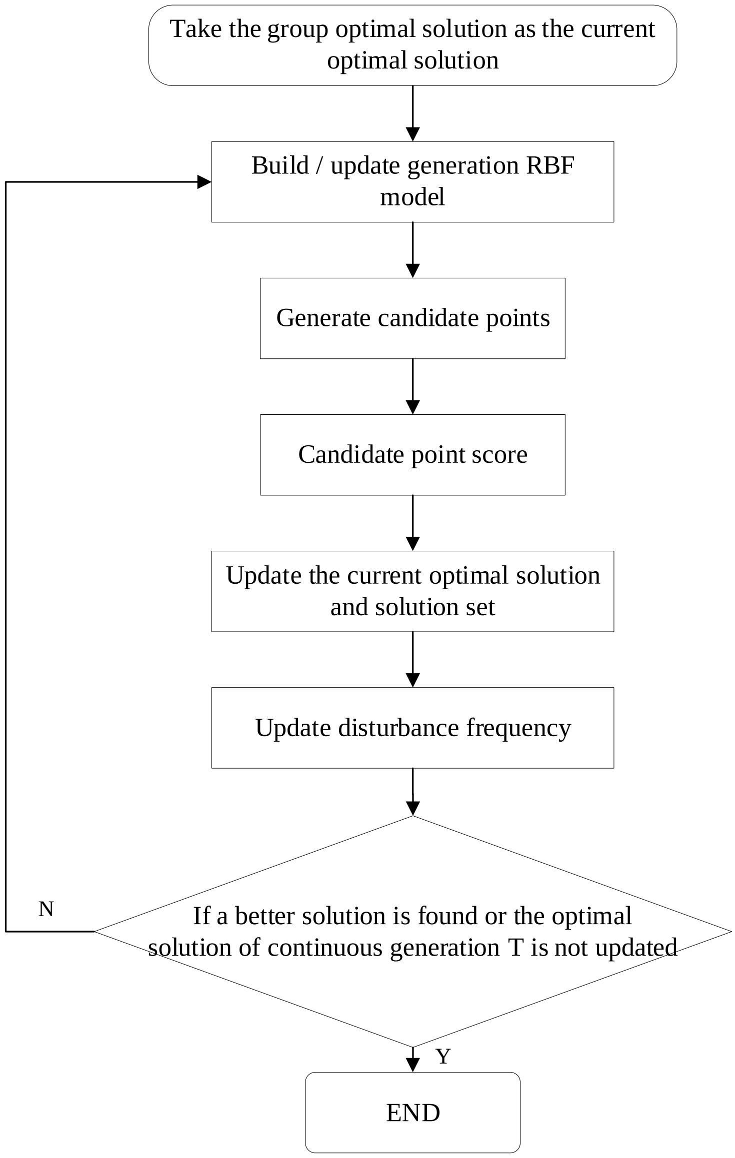

Figure 5: Algorithm flow of RBF

Predictive value scoring criteria. According to the predicted values of all alternative points obtained by RBF model, the following scores can be given to each alternative point:

$$V_n^S(y)=\begin{cases}\dfrac{S_n(y)-S_n^{\min}}{S_n^{\max}-S_n^{\min}}, & \text{if } S_n^{\max}\neq S_n^{\min}\\ 1, & \text{otherwise}\end{cases} \tag{31}$$

Among them, $S_n^{\min}=\min_{y\in E_n}\{S_n(y)\}$, $S_n^{\max}=\max_{y\in E_n}\{S_n(y)\}$.

Distance scoring criteria. According to the predicted values of all alternative points obtained by RBF model, the following scores can be given to each alternative point:

$$V_n^D(y)=\begin{cases}\dfrac{D_n^{\max}-D_n(y)}{D_n^{\max}-D_n^{\min}}, & \text{if } D_n^{\max}\neq D_n^{\min}\\ 1, & \text{otherwise}\end{cases} \tag{32}$$

Where $D_n(y)$ is the minimum distance between the candidate point $y\in E_n$ and the point in the current sample point I_n set, with $D_n(y)=\min_{y_i\in I_n}\|y-y_i\|$, $D_n^{\min}=\min_{y\in E_n}\{D_n(y)\}$,

$D_n^{\max} = \max_{y\in E_n}\{D_n(y)\}$.

Combined with the scoring criteria of predicted value and distance, the candidate points can be comprehensively scored:

$$V_n(y) = w_n V_n^S(y) + (1-w_n)V_n^D(y) \tag{33}$$

Where w_n is the weight coefficient. In practical application, each iteration w_n can take a random number in $(w_n^{\min}, w_n^{\max})$, and $w_n^{\min}$ and $w_n^{\max}$ are the minimum weight and maximum weight of the nth iteration respectively. Generally, $w_n^{\min}$ > 0.6 and $w_n^{\max}$ can be taken as 1.

Because RBF algorithm takes a long time to build and update RBF model when the time cost of fitness function evaluation is small, the number of iterations of RBF should not be too large.

5. Numerical Experiment

After completing the model construction and algorithm design of the optimal design of the power battery supply recovery network of new energy vehicles considering uncertainty, this chapter designs numerical experiments on different scales to verify the effectiveness of the model and algorithm in this paper. The CPU of the experimental platform used in this paper is Intel Core i5 2.4GHz, the 64 bit operating system of windows10 is adopted, the small-scale example is solved by CPLEX 12.6.3, and the code is run in c# of visual studio 2019.

5.1. Experimental Parameter Setting

By referring to the data in the previous literature on the optimal design of power battery supply recycling logistics network of new energy vehicles, this paper sets the unit transportation cost between facilities as 0.33 yuan / ton kilometer. Assuming that the uncertainty obeys the normal distribution, the value of uncertain factors is approximately estimated, including the demand quantity of consumer groups, power battery recovery rate The probability that the power battery is transported to other functional nodes through the recovery detection center and processing center. Other parameters in the model, such as transportation distance and recovery cost, obey uniform distribution. The specific parameter settings are shown in table 5.1. According to the set parameter distribution function, this chapter randomly generates small-scale and large-scale experimental data to carry out numerical experiments.

Table 1: Experimental Parameter Setting

Parameter	Value	Parameter	Value
c_{gh} c_{hi} c_{ij} c_{jk} c_{jl} c_{jm} c_{kl} c_{kg} (yuan / ton km)	0.33	d_{gh} d_{hi} d_{ij} d_{jk} d_{jl} d_{jm} d_{kl} d_{kg} (km)	$U(5,25)$
x_{ts}(ton)	$N(500,50)$	β_{kls}	$N(0.2,0.03)$
p_0(yuan / ton)	$U(6000,10000)$	β_{kgs}	$N(0.8,0.03)$
N_g(ton)	$U(5000,8000)$	θ_s	$N(0.9,0.03)$
N_h(ton)	$U(4000,8000)$	b_j(yuan)	$U(1500000,1800000)$
N_i(ton)	$U(1000,3000)$	b_k(yuan)	$U(1400000,1600000)$
N_j(ton)	$U(4000,6000)$	b_l(yuan)	$U(300000,500000)$
N_k(ton)	$U(2000,3000)$	b_m(yuan)	$U(100000,20000)$
N_l(ton)	$U(1000,2000)$	f_j(yuan / ton)	$U(1000,2000)$
N_m(ton)	$U(3000,4000)$	f_k(yuan / ton)	$U(2000,3000)$
α_{jks}	$N(0.3,0.02)$	f_l(yuan / ton)	$U(2000,3000)$

α_{jls}	$N(0.2,0.02)$	f_m(yuan / ton)	$U(1000,2000)$
α_{jms}	$N(0.5,0.02)$		

5.2. Small-scale Example Experiment

In the small-scale example experiment, each group of examples in each experiment randomly generates 10, 30 and 50 scenes of different sizes. In this section, CPLEX and the improved particle swarm optimization algorithm based on RBF (PSO + RBF) are used to solve the examples respectively. By comparing the solution results and running time of the two, the effectiveness of the improved particle swarm optimization algorithm for solving the problem in this paper is verified. The comparison results of small-scale example experiments are shown in Table 2.

Table 2: Comparison Results of Small-scale Examples

The Scale of Example		CPLEX		PSO+RBF		gap
t-i-j-k-m-l-g-h	Number of Scenes	obj^1	Time	obj^2	Time	
6-4-2-2-2-2-1-2	10	28721067	1	28765636	4	0.15%
	30	29237636	8	29257299	9	0.07%
	50	28901078	27	28919330	14	0.06%
8-6-2-2-2-2-1-2	10	36512774	6	36720533	5	0.57%
	30	37584289	25	37726897	13	0.38%
	50	37685342	68	37803131	27	0.31%
10-8-2-2-2-2-1-2	10	46788323	25	46941617	7	0.33%
	30	46505641	92	46700609	26	0.42%
	50	46516474	311	46699805	38	0.39%
12-10-3-3-3-3-2-2	10	55601562	92	55714283	16	0.20%
	30	56474725	579	56580912	39	0.19%
	50	56206455	1435	56353639	55	0.26%
14-12-4-4-4-4-3-3	10	65550236	378	65729058	20	0.27%
	30	66638855	3523	66762613	66	0.19%
	50	64990457	6681	65114409	96	0.19%
Average gap						0.27%

Note: （1）gap = $(obj^2 - obj^1) / obj^1$; （2）The unit of solution time is seconds; （3）The value in t-i-j-k-m-l-g-h represents the number of network nodes。

It can be seen from the small-scale numerical experiment results in the table above:

(1) When the number of different functional nodes in the network is fixed, that is, the network size remains unchanged, with the gradual increase of the number of randomly generated scenes, the solution time of CPLEX and the improved particle swarm optimization algorithm gradually

ISSN: 2664-9640

increases, which shows that increasing the number of uncertain scenes will increase the difficulty of model solution and the solution time of examples.

(2) In terms of solution time, when the scale of the example is small, the solution time of CPLEX is shorter than that of the improved particle swarm optimization algorithm. However, when the scale of the example increases gradually, the solution time of CPLEX increases rapidly and gradually loses the time advantage. At this time, when there are 4 production centers and 4 improved energy storage centers, it takes only 4 seconds to solve the problem of 4 new energy storage centers and 4 improved energy storage centers. At this time, when there are 4 production centers and 4 improved energy storage centers, it takes only 4 seconds to solve the problem. The experimental results show that the improved particle swarm optimization algorithm based on RBF performs well in solving the optimization design problem of power battery supply recovery network of new energy vehicles studied in this paper.

(3) In terms of solution quality, based on the above small-scale numerical experiments, the average gap value between the optimal solution obtained by the improved particle swarm optimization algorithm based on RBF and the optimal solution obtained by CPLEX is 0.27%, indicating that the improved particle swarm optimization algorithm has high solution quality for the mixed integer stochastic programming model constructed in this paper, which proves that the algorithm can find a more satisfactory solution in a short time.

5.3. Large-scale Numerical Experiment

With the gradual increase of the number of network nodes and random scenes, the difficulty of solving the problem will continue to grow, and CPLEX will be difficult to solve in a reasonable time. In the small-scale numerical experiment, the solution time of CPLEX is nearly 2 hours, which shows that CPLEX, an accurate solution software, will not be applied to the solution of larger-scale examples. In this section, by setting up large-scale example experiments, particle swarm optimization (PSO) and improved particle swarm optimization algorithm based on RBF (PSO + RBF) are used to solve the examples respectively, and the objective function value and solution time of the two are compared to further verify the effectiveness of the improved particle swarm optimization algorithm based on RBF. The solution results are shown in table 5.3.

Table 3: Comparison Results of Large-scale Examples

The Scale of Example		PSO+RBF		PSO		gap
t-i-j-k-m-l-g-h	Number of Scenes	obj^1	Time	obj^2	Time	
20-18-16-14-14-16-4-6	60	93133259	288	94800426	416	1.76%
	100	93177248	478	94716346	683	1.62%
	150	92820010	715	94595515	1009	1.88%
30-28-25-23-23-25-6-8	60	140575731	555	143247694	778	1.87%
	100	140827864	906	144054073	1289	2.24%
	150	140229093	1389	143878760	1949	2.54%
40-38-30-28-28-30-6-8	60	185663344	755	190717623	1067	2.65%
	100	186449720	1257	190939583	1788	2.35%
	150	185660184	1895	190648680	3805	2.62%

50-48-40-35-35-40-8-10	60	232373805	1329	242139825	2753	4.03%
	100	233379564	1712	241971541	3156	3.55%
	150	232635303	3022	241608264	7142	3.71%
60-58-50-45-45-50-8-10	60	278318668	1990	294304858	2938	5.43%
	100	279091461	3311	296289206	4681	5.80%
	150	279901280	4771	296210609	9879	5.51%
Average gap						3.17%

Note: （1）gap = $(obj^2 - obj^1) / obj^1$；（2）The unit of solution time is seconds；（3）The value in t-i-j-k-m-l-g-h represents the number of network nodes。

(1) Comparison of solution quality of large-scale examples

As shown in the above table, the average difference between the results of the standard particle swarm optimization algorithm and the improved particle swarm optimization algorithm based on response surface model is 3.17%, and the gap value tends to rise with the increase of network scale. Because when the particle swarm optimization algorithm iterates to the later stage, the particles will gradually close to the area where the group optimal solution is located, so the diversity between particles is lost and it is easy to fall into the local optimal solution. The improved particle swarm optimization algorithm based on response surface model can not only maintain the powerful global search ability of particle swarm optimization algorithm, but also have the characteristics of efficient convergence of response surface model, so that the algorithm can carry out circular conversion between global search and local search, so as to achieve complementary effect, so as to improve the solution quality of the algorithm.

(2) Comparison of solution time of large-scale examples

In order to more intuitively reflect the difference in solution time between the improved particle swarm optimization algorithm based on response surface model and the standard particle swarm optimization algorithm, this paper draws a broken line diagram to compare the solution time between them.

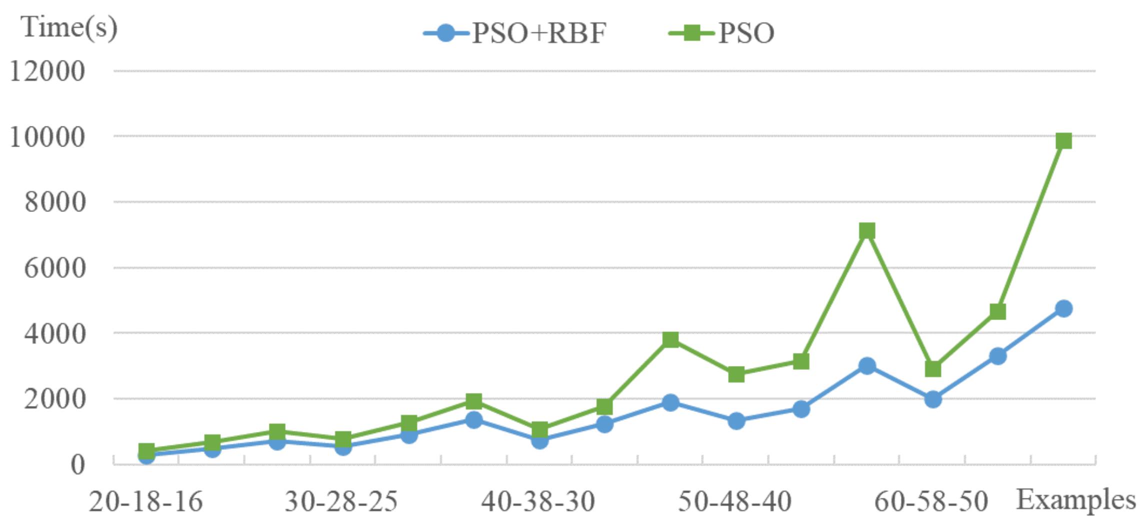

Figure 6 :Comparison Diagram of Solution Time

As shown in Figure 6, the dot polyline and square dot polyline respectively represent the solution time of the improved particle swarm optimization algorithm and the standard particle swarm optimization algorithm based on the response surface model for different sizes and scene numbers.

As can be seen from the above figure, the improved particle swarm optimization algorithm based on response surface model can maintain a fast convergence speed in most calculation examples, and the solution time is less than that of standard particle swarm optimization algorithm. With the increase of the network scale and the number of scenarios, the gap between the two solution times also shows an upward trend. It can be concluded that applying the response surface model to the improved particle swarm optimization algorithm in this paper can effectively shorten the solution time of the algorithm, save the occupation of computing resources and improve the solution efficiency of the algorithm.

In summary, the improved particle swarm optimization algorithm based on response surface model designed in this paper combines the characteristics of response surface model and particle swarm optimization algorithm, which can effectively solve the optimization design problem of large-scale and high latitude complex power battery supply recovery network.

6. Conclusion

By integrating the relevant recycling modes of power batteries in the current industry, and combining the two operation links of power battery supply and recycling of new energy vehicles into a whole, this paper carries out the optimal design of supply recycling network under the integrated mode. Based on the previous deterministic research, considering the influence of various uncertain factors in the process of supply and recovery on the supply and recovery activities of new energy vehicle power batteries, a mixed integer stochastic programming model for the optimal design of new energy vehicle power battery supply recovery network considering uncertainty is constructed, and a particle swarm optimization algorithm is designed to solve the model, The correctness of the model and the effectiveness of the algorithm are verified by designing different scale examples. According to the number of scenarios and the number of consumer groups and facility nodes in the logistics network, the scale of the example is gradually increased from less to more, and small-scale example experiments and large-scale example experiments are designed successively. Through example experiments, this paper verifies the difficulty of solving the power battery supply recovery network optimization problem considering uncertainty. At the same time, it also proves that the improved particle swarm optimization algorithm based on response surface model can obtain the satisfactory solution of this problem in a reasonable time, and improve the solution efficiency and solution quality.

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