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Based on the Final Decision of Particle Group Algorithm Applied Research

Fenghua Liu

Shandong Women's University
wsh1234wl@126.com

Abstract

Particle swarm optimization algorithm is a species of intelligent algorithm, it can solve the problem of multiple end of decision making. But the algorithm is based on each group of particles would have been the effective information hypothesis. For most of the optimization problem, by the convergence speed, set the parameters of the limit, so this paper proposes a new more volume particle group algorithm. Crowding mechanism algorithm was applied to select group of particles in the process of the optimal value, thus maintaining the dispersion, the selection of the global optimal value is more reasonable. To introduce the concept of half a feasible region, and then to avoid the traditional processing method only considers particles in area the disadvantages of the boundary value processing precision is not high. In respect of time complexity, the grouping method is adopted to choose random switching strategy, improve the efficiency of the structure of dominating sets, reduce the time complexity of the algorithm.

Key words: *Multi-objective optimization; Particle swarm optimization; Time complexity*

1. Introduction

Optimization is an old and difficult topic, it studies the problem is to find the optimal solution in many solutions, of optimization is to have multiple variables and usually need to obey the equation or inequality constraints to minimize or maximize the function of the problem. With the wide application of high-speed digital computers increasingly, make the optimization problem of study not only become an urgent need, but also a powerful tool for solving. Developed rapidly, and as a result, optimization theory and algorithm to form a new discipline [1-2].

Many final decision is one of the main research fields in optimization problem. Since the 1960 s, many final decision problem attracted the attention of more and more researchers from different backgrounds, this is because many final decision problems in real life is very common and important position. Under the same conditions, the optimized processing technology, the system efficiency, lower energy consumption, reasonable use of resources and the improvement of economic benefit, *etc*., all have significant effects. Such as factory's minimum cost and maximum efficiency problem is a typical multiple final quantity decision problem, in addition to social development and national economy in the long term development plan optimization and decision problems, *etc*. Generally speaking, science and engineering practice of optimization problems are mostly more decision-making and decision-making problem. And these actual problem is very complicated, difficult, more investment is needed to solve the problem of energy. Therefore, solving the problem of multiple final quantity decision is a very scientific research value and practical significance.

With the expanding of human living space and know the world and transform the world to broaden, conventional methods such as evaluation function method, the layered sequence method has been unable to deal with complex issues facing people, so efficient

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optimization algorithm become one of the research eventually amount of scientific workers.

Evolution of organisms in nature by itself to adapt to the surrounding environment so as to constantly moving forward, evolutionary algorithm is gradually developed based on this idea, a kind of random search technique, is a kind of mathematical simulation of biological evolution process, and they are simulated by the individual groups composed of collective learning process. The emergence of evolutionary algorithms for those hard to find the problem of traditional mathematical model points out a new way, for the same is true of many final decision in this area, because of the evolutionary algorithm has the advantages of solving many final decision problem, and received considerable attention, which leads to a new class of research and application, referred to as many final evolutionary optimization [3-5].

Evolutionary algorithm has been used to solve complex single final quantity and quantity decision making problems, in this paper, we study the particle swarm optimization algorithm is in 1995 by the American social psychologist proposed by Kennedy and Eberhart electrical engineer, from the simulation of the migration and accumulation in the process of the flock foraging. Its convergence speed is fast, easy to implement and only a few parameters need to be adjusted, so as soon as a new research hotspot in the field of evolutionary computation, has been widely used in the final volume function optimization, dynamic environment optimization, neural network training and many other fields. One of the most application prospect areas including final amount more optimization, system design, classification, pattern recognition, decision making and simulation, *etc*.

Many final particle swarm optimization algorithm is a new kind of multiple final quantity decision algorithm, and the more traditional end decision method compare and other evolutionary optimization algorithm which has the following advantages:

(1) In the optimization process, each particle update by own experience and group, has the function of learning and memory;

(2) Similar to genetic algorithm, the search process is also from a set of iteration to another set of solutions, using the method of treatment group, multiple individuals at the same time, with the nature of parallelism.

(3) On the encoding particle swarm algorithm is simpler, can be directly based on real number encoding optimization problem;

(4) Algorithm has the characteristics of general, more suitable for the vast majority of final quantity decision problems;

(5) For population initialization not as sensitive as other evolutionary algorithms, can achieve faster convergence rate;

2. Related Works

2.1. Particle Swarm Algorithm

Particle optimization algorithm is the result of simulation of birds feeding behavior. Imagine such a scene: a flock of birds in the random search food doesn't know where to put food, only a piece of food in the search area. All the birds do not know where the food, but they know how far is your current position from food. So what is the optimal strategies to find food. The most simple and effective method is to search for the nearest food bird's surrounding area.

Particle swarm optimization algorithm is used to get enlightenment from this model and is used to solve optimization problem. In particle swarm optimization algorithm, the optimization problem of each solution is considered to be a bird in the search space. We call this the particles. Each has its own position and velocity (decided to the direction and distance of flight), and a determined by be optimized function adaptive value, and know ourselves so far found that the best location and the location of the now. This can be regarded as a particle flight experience. In addition, each particle also know so far all particles found in the best position of the entire group. This can be regarded as a particle companion's experience. Each particle with the following information to change your current position:(l) The current position; (2) The current speed; (3) The distance between the current position and his best position.(4) The distance between the current position and group the best position [6-8].

Particle swarm optimization algorithm is a population optimization algorithm. Particle group can be thought of as particle within the G, convey information according to certain rule, according to the changes of the information to change the state itself since the organizational behavior. Particle group mainly from information by each particle individual extremum matrix composed of $P=(p_1, p_2, ...p_n)$ .Basic particle swarm optimization algorithm in particle information extracted from the Q have group global extreme value of Q and the optimal position, every particle has its own experience, the optimal location individual extreme value Q. Group optimal position allows the particles to form particle group of rapid convergence, and the global extremal neighborhood search; Individual experience, the optimal location to ensure grain unapt too fast convergence to a group of optimal, and fall into local minimum point, make particles in one iteration of the area between the individual extremum and global extremum search.

Particle swarm optimization algorithm is a search algorithm, it has effective search performance, because of group cooperation. As literature, social behavior, there are two main purposes: one is in the process of every individual to search food to assist other members of the group, the second is group cooperation can improve the search efficiency. In other words, each particle can provide information for group and each particle can assist other particles to search again.

Suppose in a G final volume of the search space, there are m particles that make up a tribe, of which the ith a particle is expressed as a D vector $x_i=(x_{i1}, x_{i2}, ...x_{id}), i=1,2,...m$, the ith particle with a position in the searching space of O is x_i. In other words, the position of each particle is a potential solution. Bringing x_i to adapt to a final quantity function can be computed values, according to the size of the adaptive value to measure the pros and cons of x_i. The ith particle is also a O dimensional vector, remember to $v_i=(v_{i1}, v_{i2}, ...v_{id})$. Remember the case of a particle to date I search to the optimal location for $p_i=(p_{i1}, p_{i2}, ...p_{id})$, the particle group so far to search the optimal location for $p_g=(p_{g1}, p_{g2}, ...p_{gd})$.

Using the following formula for particles operation:

$$v_{id}=w*v_{id}+c_1*r_1(p_{id}-x_{id})+c_2*r_2(p_{gd}-x_{gd}) \tag{6}$$

$$x_{id}=x_{id}+v_{id} \tag{7}$$

If the formula from the point of view of sociology in the second part (particles I the distance between the current position and their best position) as the cognitive part, say particle motion is derived from the part of the experience; The third part (particles I the distance between the current position and group best position) for the social part, say particle movement from the other particles experience part of the group, show the knowledge sharing and cooperation. Particles is through the best experience of his own experience and companion to decide the next movement. This is similar to how human decisions, people are also usually through integrated itself has some information and information from the outside to make a decision. Finally, listed the main steps of basic particle swarm algorithm.

(l) Initialize a particle group, namely the randomly generated the initial position and velocity of each particle.

(2) According to the final quantity function to evaluate the fitness of each particle;

(3) For each particle, the particles and the fitness experience of individual extremum, if good, will the location as the current best position;

(4) For each particle, its fitness with whole grain group of experienced global extreme value to set the value of the optimal solution;

(5) According to the formula to calculate the speed and position the new speed and position:

(6) As to the terminating conditions (usually in the form of a preset maximum iterative algebra or minimum error min value), otherwise returns (2) a new iteration.

2.1. Multi-final Decision-Making Mechanism

Optimization process is in more than one possible choice to find for some final amount is the optimal solution of the problem, the final amount of the number may be only one or more, if only consider a quantity, is called a single optimization problem, this kind of problem has got the in-depth and extensive research, on the other hand, if there is the final amount of more than one and need to handle, at the same time becomes more final decision problem.

Single end quantity optimization problems usually can be formulated as the following form:

$$\max z = f(x) \qquad s.t. \qquad g_i(x) \le 0, i = 1, 2, \ldots m \tag{1}$$

$x \in R^n$ of them were with n vector of decision variables, the function $f(x)$ is the final quantity, $g_i(x)$ is a function m inequality constraints, they form the feasible solution region. Usually expressed in decision space by S feasible region, said the following:

$$S = \{x \in R^n \,|\, g_i(x) \le 0, i = 1, 2, \ldots m, x \ge 0\} \tag{2}$$

Do not break general, many final decision problem can be expressed as the following form:A given decision vector $x = [x_1, x_2, \ldots x_m]^T$, it satisfies the following constraints:

$$g_i(x) \le 0, i = 1, 2, \ldots k \tag{3}$$

$$h_i(x) \le 0, i = 1, 2, \ldots k \tag{4}$$

Equipped with m optimization quantity, and the m optimization quantity may be conflicting, optimize the final quantity can be represented as:

$$f(x) = [f_1(x), f_2(x), \ldots. f_m(x),]^T \tag{5}$$

Seeking to $x^* = [x_1^*, x_2^*, \ldots x_m^*]^T$, $f(x^*)$ in meet the constraints, and at the same time.

From (1) the definition we can see that in the final decision making problems with single final amount more optimization or have very big difference, when only one final amount, people are looking for a best solution, the solution is better than all the other solutions. And when we solve many final decision problems, are due to multiple end quantity and quantity cannot compare and conflict between the phenomenon, do not expect the minimum point of repeating them in together, namely can't reach the optimal solution at the same time; Even sometimes have the opposite situation, that is, to a final quantity function is the most advantage, function on the other end is almost. To make all the final quantity function at the same time it is impossible to achieve maximum. Many end algorithm core is to coordinate the end of the relationship between the function, find out the final volume function can reach as far as possible is bigger (or smaller) the optimal solution set, a solution may be on one of these is the best, but on the other end is the worst, don't have at all on the final quantity is the optimal solution. When, therefore, have more than one final quantity, there are usually a bunch of compare not simple solution. This solution is usually referred to as the control solution [9-12].

For final decision problem, from the perspective of mathematics, many final decision effective solutions for all of the solution, the solution is acceptable solution, there is no any difference between different yet people often require one or more of the final solution to guide practical work. Select one from many final decision efficient solution concentration decision making is the process by which one or more of the solution. Guide decisions should be on a deeper understanding of the actual problem, plus his be fond of preference or empirical knowledge, select its think is the most suitable solution. Get final quantity decision more efficient solution set is known as the solution process or optimize the process, it often and decision-making process of mutual cooperation, so as to find the people need the final solution. According to the decision makers in the process of optimization, participation way, depends on the optimization and decision making is how to combine the two process, many final decision method can be divided into four categories:

Before optimization decision: many prophecies, quantity decision of multiple were merged into a single optimization problem, it contains the be fond of policymakers implicit information. After the optimization decision: in the absence of any preference information optimization. The results of the optimization process is the set of candidate solutions, and then by policymakers ultimately make a choice. In the process of optimization for decision: in the process of optimization, gives some preference information. Every step of the optimization process, get some compromise, on this basis, gives a deeper preference information to guide the deeper optimization. There is no clear preference information: no obvious belongs to the type of method, do not need any method of decision-making information. Or more simply divided into two categories: (l) Considering the preference in the process of optimization, the result was a final solution method based on preference; (2) In the optimization process does not consider the preference, directly by a non dominated solution set production method.

The method based on preference is trying to get a final solution, production method is trying to get a non dominated solution set. If can pass some criteria to determine relative importance between the final amount, you can use these guidelines to get the final solution. If there is no rule of any information, so can only use production for a non dominated solution set and carries on the inspection, satisfactory results are obtained.

Before the application of evolutionary algorithm, more than most of the traditional final quantity are based on the preference of decision algorithm, which based on the preference information provided by decision makers, through a certain method to convert many final decision problem into a optimization problem, or a series of single terminal quantity can be solved by using the mathematical programming to obtain the final solution. Many final decision method based on the preferences including the evaluation function method, stratified sequence method, several methods, such as amount of programming.

Evaluation function method in line with the final amount into a single final amount of thought, will be difficult to unity of multiple end into a single end use of the existing quantity optimization method is easier to solve the problem of the amount of single terminal. Into a single final amount is the process of a real function using the preference information of decision makers to provide structure, the process of making the process of looking for policymakers satisfactory solution is equivalent to solve in the real function for the new amount of single terminal problem. Evaluation function is to use an evaluation function to concentrated reflect different factors such as the importance of the final quantity, and minimizing the evaluation function, the optimal solution is obtained. Commonly used evaluation function method is: the main method of terminal, linear weighted method, the minimax method, ideal point, *etc*.

a. the main method

According to the practical significance of the problem, determine a major final amount and the rest in a certain amount of within the acceptable limit as constraints.

b. the linear weighting method

Linear weighting method is the simplest and most basic is also the most widely used multiple final quantity decision algorithm. Its core thought is important decision makers in $f_i(x)$, according to the final quantity, gives a nonnegative weights respectively under the different weights of combination to solve the single final quantity optimization problem can be obtained by a set of solutions. If asking questions with convexity, then theoretically by the method iterative can get a complete non dominated solution set. However, the problem does not meet the convexity, will not be able to guarantee the end up with a satisfactory solution set. The algorithm has several obvious disadvantages: on the one hand, the little change of weight parameters can cause for final quantity vector of a significant change; Different weighting parameters of significant change, on the other hand, might get similar solution vectors. Therefore, weight evenly distributed collection tend not to produce a more uniform distribution quantity decision always efficient solution set.

c. Extremum method

In extreme value method is the most unfavorable for the final amount of cases to find the most powerful solution.

Layered sequence method is characteristic of the flow function is not equal is optimized, but according to the different priority level is optimized. Before the final amount of the first layer and the optimal solution, after reaching the final volume under the condition of the second final amount of the optimal solution, and so on until the end of the final solution to get the optimal solution. Commonly used stratified sequence method has fully layered method, hierarchical evaluation method and the key method, *etc*. Which completely layered method of each priority level, only a final. Using this method can obtain satisfactory commonly optimal solution, but there is a fault, the method of the current problem of the optimal solution is the only time, behind solving loses its meaning.

Weights based on the final amount of planning, if the final quantity level is more final decision reference point, or offset variable is positive, can guarantee to get the solution of the final decision efficient solution. This method is easy to understand, policymakers easy decision, but the weight parameters are still hard to set up correctly, and there is no practical significance.

Use the traditional method based on preference to solve many final decision problems can make full use of the user to master decision-making information, if it meets the requirements of decision optimization results can be obtained directly, avoids the optimized decision step. In addition to traditional methods and easy to implement, fast computing speed of priority. But the traditional method has several major defects:

(l) Practical problems due to the physical significance of the different final quantity and unit of measure is often different, cannot be directly compared between final quantity or weight. Although you can use the dimensionless processing of final quantity function to solve, but it increases the complexity of the algorithm, and will cause the change of the amount of space eventually lead to cannot use the normal decision-making information.

(2) The algorithm requires the user to provide accurate decision-making information, but often fail to provide certain conforms to the actual needs of decision-making information, cannot be accurately set up mathematical model of optimization problems.

(3) Most of the algorithms can only get a local optimal solution, in order to avoid falling into local optimum, expand the neighborhood size is a common method, but with the increase of neighborhood, the complexity of the algorithm and presented the index power will also increase.

(4) Many of the traditional methods can only be applied to the corresponding small problem sets, poor generalization. For a real-world optimization problems, we must try many different ways, or even to invent new methods to solve, this is obviously unrealistic, cumbersome. We need another method to overcome such difficulties.

Production method in the optimization process does not consider the end of the relationship between, there is usually no preference information available, multiple quantity function is optimized at the same time, dominate the dominant concept and usually used to distinguish the pareto solutions and other solutions. Production method will produce a series of non inferior solution for decision makers choose the solutions they need. Production method can be realized through some simple way, such as change the weight coefficient of the linear weighting method and obtained a series of non inferior solution set. But due to the defects of the method based on preference, these methods can achieve good non inferior solution set, easy to fall into local optimum, especially for the less effect of the solution of the problem of convex function. Using production method for final decision, more simply to a problem, because as long as more than the decision problem model is determined, the non inferior solution set is determined, unlike the method based on preference, if the preference change, must according to the new preference information to optimize again. The production method of defects are often require a lot of computation cost, the performance is more obvious in high dimensional complex problems.

3 Improved the Final Amount of Particle Swarm Optimization Algorithm

Improved particle swarm optimization algorithm based on final amount will more decision-making dominations relation structure disposal solution set, USES the external set to save the current find a non dominated solution set, the control concepts used to update the external collection, the algorithm can keep good distribution, by introducing the concept of half a feasible region design selection operator to deal with constraint conditions in order to increase precision, the crowded system and tabu algorithm is applied to the global extremum and the selection of individual extremum method avoid falling into local optimal solution of inferior quality, and put forward the random selection strategy grouping the dominating sets the structure construction method to speed up the algorithm efficiency. Listed in this chapter, first to improve the final amount of the main process of particle swarm optimization, and then introduce algorithm adopted in each item by item technology, finally using the standard test functions to experimental analysis, verify the feasibility of the improved algorithm is proposed in this paper, the practicability and advanced.

Hybrid particle swarm optimization process of the final amount:

(l) Initialize particle group, the population of size N:

(2) The application of selection operator, get enough good individual;

(3) Of each particle in the particle group updates its velocity and its position:

(4)Calculate each particle fitness function value;

(5) The dominating sets: grouping with random selection strategy to find out the population of particles into the non dominated solution set not domination;

(6) To update the individual extremum, use control concept here. For each particle, if the current position of particle I dominate its individual extremum position, update their individual extremum; if both as a dominant relationship, when both in feasible region or half the feasible region, randomly selected individual extremum; when both a feasible region in a feasible region or another one in another half a feasible zone in the feasible region, the selection of the former; when both in the feasible region, and its d.

(7) To update the external sets, the group of dominating sets in - dominance relations into external set;

(8) To update the global extremes, using crowded mechanism and tabu algorithm in an external focused randomly select a particle as a particle;

(9) According to iterate formula for particles and transferred to exit (2) suspended until meet conditions.

External set saving is the best result algorithm runs in each generation, the algorithm of iterative operation is completed, the external focus all of the particles is finally get the results of the algorithm.

In the algorithm, a total of set up three sets were used to hold grain group, the dominant, external sets. Particle group is the main part of the executive search, the disposal and external sets is to save the main body of the search results. Algorithm starts running, the first random initialization of particle group and related parameters, and then find out all the control of particle group of particles and insert a command set, the dominating sets represents in the operation of the algorithm in this generation to search the best part of the grain, but also must isolate algorithm have so far found the optimal portion of the particles, so you also need to insert of the dominant particles obtained from each generation of external focus, and global extreme value should be algorithm to find solutions, obviously the external set as global extremum candidate set is very appropriate, particle group and under the guidance of extremum search continuously more optimal solution, and then into the next cycle [13-15].

4. Experiment and Result Analysis

Evaluation the performance of more than a final amount of evolutionary algorithm can be from the convergence, the distribution and time efficiency of three aspects to consider. This paper adopted three quantitative evaluation criteria:

1. The generational distance: to final solution set estimation algorithm and global optimal regions not bad the approaching degree, calculated as follows:

$$GD = \frac{\sqrt{\sum_{i-1}^{n} d_i^2}}{n} \tag{6}$$

N is the number of solution concentration of the individual, d_i is every individual to the global optimal solution of minimum Euclidean distance of inferior quality. GD value means that the smaller the solution set, the more close to the global optimal regions is not bad, if the solution for GD=0 means algorithm is on the global optimal regions is not bad, this is the most ideal situation.

2. The spacing: by calculating the solution concentration of each individual and neighbor to the change of distance of the individual evaluation of solution set on the distribution of the target space, its functions are defined as follows:

$$SP = \frac{\sqrt{\sum_{i-1}^{n} (d - d_i)^2}}{n-1} \tag{7}$$

The number of solution concentration is n individuals, d; Is every individual to the global optimum solution of the non inferior minimum Euclidean distance. D is the average of di. If SP=0 solution concentration equal all the distance between the individual and uniform distribution, SP the smaller the value of the solution set distribution more uniform.

3. CPU - Time: algorithm running Time.

Chose a constraint F1 standard test functions to test the effectiveness of the algorithm.

$$F1: \quad \min f_1(x) = 2 + (x_1 - 2)^2 + (x_2 - 2)^2$$

$$\min f_2(x) = 9x_1 - (x_2 - 1)^2$$

$$g_1(x) = x_1^2 + x_2^2 \le 225$$

$$g_2(x) = x_1 - 3x_2 + 10 \le 0$$

Experimental loop iteration 100 times, average number of particles take 100100 times test results: GD = 0.008241, SP = 0.00193, time = 0.00193. Comparison of linear weighting and MOPSO results as shown in Figure 2, 3. In this paper, the improved algorithm to optimize schematic uniform distribution, a collection of particles. Can see that the proposed method have significant advantages on the degree of approximation, dispersion, but slightly longer on operation time. As shown in Figure 1 to 100 times a typical arithmetic of optimization results.

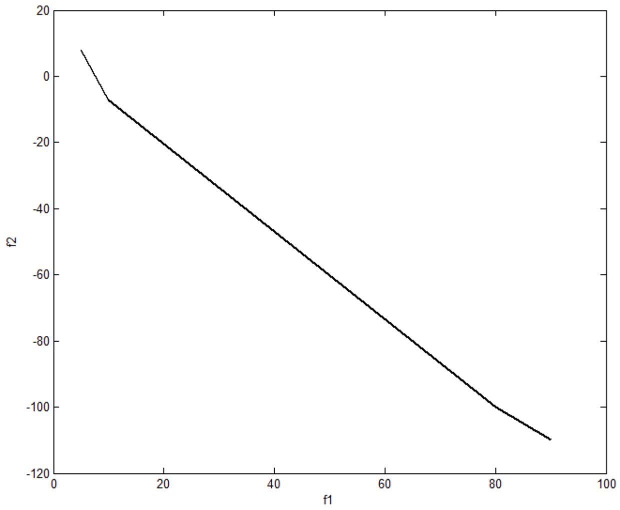

Figure 1. Improved MOPSO

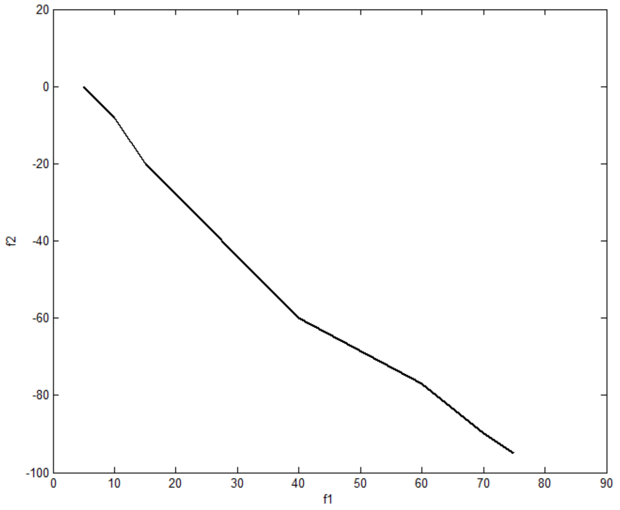

Figure 2. MOPSO

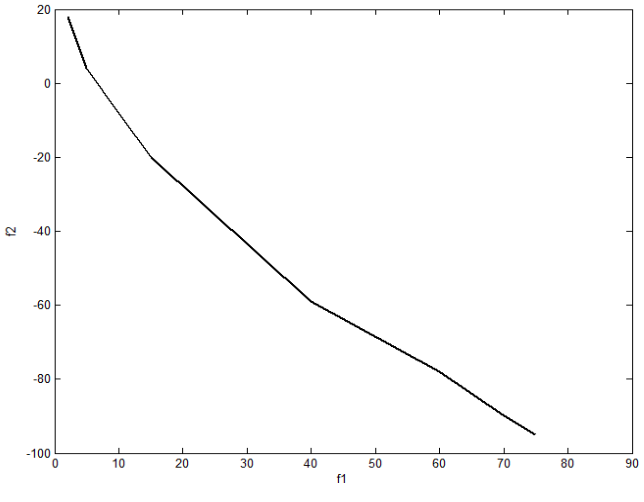

Figure 3. The Weighted Liner

5. Conclusion

Solve the constraint problem of this paper designed a hybrid particle swarm algorithm of the final amount, selection operator is used to deal with constraints, in the process of selecting global extreme value and the individual extremum join tabu algorithm and congestion mechanism, construct the dominating sets adopt random selection strategy when exchange grouping, use external elite set to save the result. Experiments show that the algorithm has good convergence and keep the solution of the distribution, can effectively solve the unconstrained and constrained quantity decision problem.

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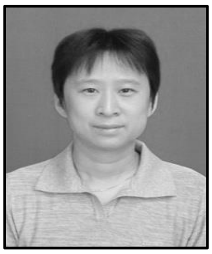

Fenghua Liu, received her B. S. degree in computer science and M.E degree in computer software and theory from Shandong University, China in1997 and 2006 respectively. She is currently researching on Data Mining, Cloud Computing and Software Engineering.