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ORIGINAL ARTICLE

Multi-objectives optimal model of heavy equipment using improved Strength Pareto Evolutionary Algorithm

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Abstract The problem of injection molding machine's multi-objective optimization is very important. A triple-objective optimization model with the largest mould moving speed and injecting capacities and the smallest injecting power has been created. The optimized design constraints of the optimal model are summarized. The computational efficiency of Strength Pareto Evolutionary Algorithm (SPEA) is improved by using rough set-based support vector clustering method. The number of external stocks is reduced. The optimal Pareto solution is determined by eliminating the uncertainty in the artificial priority election. The multi-objective optimization of the HT1600X1N injection molding machine is taken as an example. The SPEA-RSVC-II which is the mixed algorithm of Strength Pareto Evolutionary Algorithm and Ro′ugh-based Support Vector Clustering is applied. It shows that the new method could accelerate the population clustering operation effectively and improves the efficiency of optimized calculation.

Keywords Support vector clustering · Strength Pareto evolutionary algorithm · Multi-objective · Optimal design · Injection molding machine

1 Introduction

Injection molding is a complex process which requires equipment with high production efficiency and adaptability. The injecting device's main function is to complete the plasticizing and injection of the plastic. So, it must have an excellent plasticizing ability and precise measurement, and can provide sufficient pressure and velocity for the plastic to melt in the injection process. The clamping device must ensure that the mold can be reliably open and close. Therefore, it should have enough clamping force to prevent the mold from being opened under the pressure of the melt during the injection process, which may generate flash for the product or decrease the injection precision.

Injection molding machine has been widely used in all kinds of areas such as the defense industry, aviation, transportation, machinery, construction, agriculture, and for consumer products. An injection molding machine must have three basic functions: plasticization, injection, and molding. They are respectively comprised of mechanisms like injection, clamping, power, electrical control, and so on. In considering the overall performance of the injection molding machine, in order to satisfy the requirements of fast forming speed and high product quality, the machine must guarantee to provide sufficient and injection velocity. The injection molding machine is mainly comprised of two parts: the injecting device and the clamping device. In addition to

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meeting the plasticization and injection pressure requirements, the restrictions such as injection power, injection precision, and clamping force must be taken into consideration. There is the multi-objective optimization problem of the injection molding machine's overall performance.

Recently, many scholars have studied on multi-objective optimization of mechanical products. Linear weighting method, constraining method, and mixing method are the traditional methods. The linear method transforms multiple objects into a single object. The optimal solution sets with different object weights are acquired through transforming the weight coefficients and running repeatedly [1], but it is hard to achieve Pareto frontier with good distribution. By establishing the constraint relations among various optimization objectives, the constraining method sets up a conflict resolution mechanism to achieve the multiple objectives' optimal solutions in the system [2]. However, the constraint relations in the system are always very complex, and they may generate coupling relations which made them impossible to achieve the optimal solutions. The mixed methods combine the linear weighting method and the constraining method. A complex optimization model with weight coefficient transformation and constraint rules is established. It can achieve the optimal solution set under different weight conditions by meeting the constraint rules. But this method has the same inherent application defects as the linear weighting method and the constraining method. In the methods of solving the multi-objective optimization problem, the appearance of Multi-Objective Evolutionary Algorithm (MOEA) has solved the inadequacies of the traditional methods.

From the beginning of the first design of Vector-Evaluated Genetic Algorithms (VEGA) by Schaffer in 1985, the multi-objective evolutionary algorithms have gone through the stagnation from 1985–1994 and the development from 1995 to nowadays. It has gained widespread concern and application. The multi-objective evolutionary algorithm can achieve the Pareto frontier which approximates the optimal solutions and has uniform distribution in a single run. Nowadays, there are several representatives such as Multi-Objective Genetic Algorithm (MOGA) [3], Nondominated Sorting Genetic Algorithm (NSGA) [4], Non-dominated Sorting Genetic Algorithm II (NSGA-II) [5], Niched-Pareto Genetic Algorithm (NPGA) [6], Pareto Envelope-based Selection Algorithm (PESA) [7], Strength Pareto Evolutionary Algorithm (SPEA) [8] and so on.

1. MOGA is proposed by Carlos M F and Peter J F. The rank of the individual equals the number of the chromosome which dominates it in the current population, and the rank of all the non-inferior individual is 1. The advantages of MOGA are those that the algorithm can be easily implemented and has a high efficiency. Its disadvantages are those that the algorithm is vulnerable to influence of the Niche size and the Pareto frontier is not ideal.
2. NSGA is proposed by Srimivas and Deb. The individuals are classified into some levels. The decision-making vector space introduces the sharing function. The diversity of the population is maintained. Neglecting all of the classified individuals, the non-inferior individuals in the other levels are analyzed until all the other individuals are classified. The advantages of NSGA are those that the number of the optimization objectives is not constrained and the non-inferior solutions are uniformed distributed. Its disadvantages are those that its computational efficiency is low, the elite preservation strategy is not used, and the sharing parameters need to be predetermined because the Pareto sorting needs to be done many times.
3. NSGA-II is the improved version of NSGA. The solution sets must be determined. The elite preservation strategy is used to retain the best parent individuals and subindividuals.
4. NPGA is proposed by Jeffrey H. The championship selection mode based on Pareto dominant is used. The non-inferior solution selection is based on the part of population. Its advantages are those that some good non-inferior optimal solution domain can be quickly found, and it is able to maintain a longer population update period. But its disadvantages are those that the sharing parameters need to be set, an appropriate size championship has to be selected. Therefore, the practical application of this algorithm is limited.
5. PESA is proposed by Corme. The small internal population and the large external population, as well as the phenotype space super lattice partition method are used. The population diversity is maintained. The external population determines the mode and selection methods of the diversity.
6. SPEA is proposed by Zitzler. With external population to achieve elite preservation strategy, non-inferior individuals in each generation to external population are copied. The fitness of each individual in the current population is computed by the sum of the strength of the non-inferior solutions which dominate it in the external population and the computation of fitness value also take the degree of approximating the Pareto frontier and the solutions' distribution into consideration. The advantage of SPEA is that it ensures the distribution along the Pareto frontier by using the distance-based niche radius and Pareto dominance. But its disadvantage is its computing efficiency is determined by the number of non-inferior solutions in the external population. When there is large number of

non-inferior solutions in the external population, this algorithm will reduce the selection pressure and slow the convergence rate.

Scholars in the world put forward many new ideas and new methods in the performance design of mechanical products, all of them are valuable. Lun G C [9] incorporated gene fragment recombination and several antibody diversification schemes to improve the balance between exploitation and exploration. Moreover, the concept of cytokines is applied for handling constraints. The effectiveness of CMOIA is evaluated through six test functions and two well-known truss sizing optimization problems. Liu Y M [10] proposed a modified genetic algorithm based on the traditional genetic algorithm. The operating domain is defined and changed to be around the optimal point in its evolutionary processes so that the convergence speed and accuracy are improved. The modified genetic algorithm is used for the optimization of milling parameters and simulation, and experimental results show an improved performance. Optimization of cutting parameters represents a key component in machining process planning. Wang N [11] presented a neural network-based approach to multiple-objective optimization of cutting parameters. First, the problem of determining the optimum machining parameters is formulated as a multiple-objective optimization problem. Then, neural networks are proposed to represent manufacturers' preference structures. To demonstrate the procedure and performance of the neural network approach, an illustrative example is discussed in detail. The increased use of flexible manufacturing systems (FMS) to efficiently provide customers with diversified products has created a significant set of operational challenges. Jerald [12] conducted on design and operational problems of automated manufacturing systems; many problems remain unsolved. In particular, the scheduling task, the control problem during the operation, is of importance owing to the dynamic nature of the FMS such as flexible parts, tools, and automated-guided vehicle (AGV) routings. The FMS scheduling problem has been tackled by various traditional optimization techniques.

Using the elite preservation strategy, SPEA makes the new generation more effective than the previous. SPEA improves the computation effect, so it is very popular in current days. However, due to the multi-objective optimization problem of the injection molding machine's overall performance, which is quite complex, and the scale of the non-inferior solutions in the external population is very large, a new algorithm SPEA-RSVC-II that combines the SPEA and Rough-based Support Vector Clustering (RSVC) [13] is proposed in order to apply SPEA to practical engineering problems in a more effective way. This algorithm deleted the similar individual in the optimization computing process, which constrained the external non-inferior solutions' scale into a certain size, improved the computation efficiency of multi-objective optimization, and acquired the optimization design results of the injection molding machine's overall performance. Moreover, the Pareto optimal solution selection mechanism, which is based on set theory, excluded the uncertainty in the artificial election process.

2 Description of multi-objective optimal model

2.1 Optimization objectives

The main criteria of evaluating the injection molding machine model are mould moving speed, injecting capacity, and injecting power. The whole structure of injection molding machine is very complicated, with lots of parts and components, and includes horizontal, vertical, angular, and multiposition injection molding machines. Its common functional structure is shown in Fig. 1 [14].

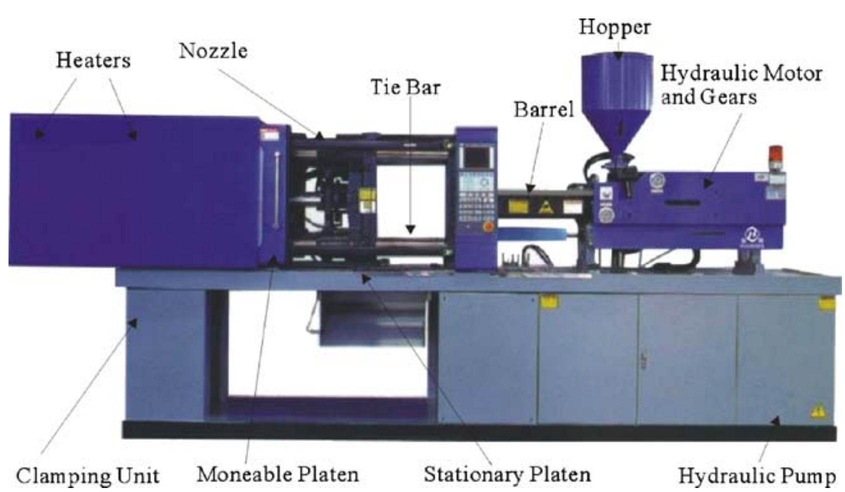

Fig. 1 Structure of injection molding machine

1. Mold moving speed is the capacity of plasticizing materials. Large mould moving speed could guarantee the materials' supply in the fast-speed and high-pressure injection molding. It is an important indicator of the plasticizing performance for the injecting device. In the whole injection molding cycle, the plasticization should ensure that there are sufficient plastic materials which are uniformly melted to prepare for the injection within the required time frame.
2. Injecting power is the average value of the power which is needed in various stages of the shaping. It is mainly determined by the plasticizing capacity and the injecting pressure. In order to ensure large plasticization and large injecting pressure, the injecting power should be minimized. The injecting power will gradually increase, which brings large additional power consumption.
3. Injecting pressure is the pressure on the materials in the machine barrel. It must provide enough injecting speed. Large injecting pressure would increase the production efficiency and improve the product-shaping quality. Injecting pressure plays an important role in the injection molding. During the injection process, it must overcome all the flow resistance when the melting material flows through various channels from the machine barrel to the mold cavity.

To ensure the injection molding machine's overall performance of fast shaping and high production quality, the optimization goal is that the injecting power should be decreased when the plasticization and the injecting pressure are improved. The expression of optimization objectives for the injecting power, plasticizing capacity, and injecting pressure is as follows [15]:

Mould moving speed (cm^3/s):

$$Q = \frac{\pi^2 D_\mathrm{s}^2 h_3 \tan\theta}{2} - \left(\frac{\pi D_\mathrm{s} h_3^3 \sin^2\theta}{6\eta_1} + \frac{\pi^2 D_\mathrm{s}^2 \delta^3 \tan\theta}{6\mu_2 e}\right) q_\mathrm{L} \tag{1}$$

$$\text{Injecting capacity (MPa)}: p_i = \frac{F_0 p_0}{F_\mathrm{s}} n = \left(\frac{D_0}{D_\mathrm{s}}\right)^2 p_0 N \tag{2}$$

$$\text{Injecting power (Kw)}: \; N_i = F_\mathrm{s} p_i v_i = q_\mathrm{L} p_0 \times 10^{-3} \tag{3}$$

n (r/m) is rotating speed of the screw stem; θ (°) is the lead angle; δ (cm) is the gap from the screw stem to the machine barrel; F_s (cm^2) is the cross-sectional area of the screw stem; p_0 (MPa) is the working oil pressure; N is the number of injection tanks and v_i (cm^3/s) is the injection speed; D_s (cm) is the diameter of the screw stem; h_3 (cm) is the depth of the measurable screw channel; e (cm) is the axial width of the screw stem; L_3 (cm) is the length of the measurable section; q_L (cm^3/s) is the theoretical injection speed; F_0 (cm^2) is the effective area of the piston of the injection tank; D_0 (cm) is the inner diameter of the injection tank; η_1 (Pa s) is the effective viscosity of the melting materials in the screw channel; η_2 (Pa s) is the effective viscosity of the melting materials in the gap.

2.2 Optimal constraints

In order to ensure the usability of optimization results of the injection molding machine, the constraints must be established during the optimization process.

Inner diameter of injection tank D_0: in order to make full use of the injection device's ability, D_0 must meet the equation constraints as Function 4;

$$D_0 = D_s \sqrt{\frac{p_i}{N p_0}} \tag{4}$$

Number of injection tanks N: N should be 1 or 2;

Plasticizing capacity Q: Q should meet the inequality constraints shown as Function 5. The correction coefficient k=0.88;

$$Q = \frac{1}{2}\pi^2 D_\mathrm{s}^2 h_3 \sin\theta \cos\theta \cdot k \geq Q^{\min} \tag{5}$$

Theoretical injecting speed q_L: in order to get products with homogeneous density and stable size, the size, and number of injection tank must meet the equation constraints.

The constraints between injecting pressure and plasticization are shown as Table 1;

3 SPEA-RSVC-II of multi-objective optimal

3.1 Pareto dominant relation and individual fitness function

Define the necessary and sufficient conditions of solution x^0 dominating x^1 (namely, $x^0 \succ x^1$) [16].

There is at least one objective value in x^1, which is strictly bigger than the corresponding objective value of x^0.

Table 1 Range constraint relations

Injecting pressure (MPa)	Plasticization (cm^3/s)
1,300~1,400	808.9~3,050.6
1,400~1,500	180.9~808.9
1,500~1,600	20.2~180.9

The Pareto optimal solution set is a set in which each solution is not dominated by another one.

There are no dominant relations between the individuals; the density value of individual is just its fitness value. The fitness functions of the external population and the internal population are shown as follows:

The fitness values of the individual in the external population are proportional to the number of the individuals in the internal population which are dominated by it.

The fitness values of the individuals in the internal population are the sum of the fitness values of all the individuals in the external population.

3.2 Computational procedures

SPEA-RSVC-II expresses the design constraints in the multi-objective optimization problem of the injection molding machine's design. In order to avoid the uncertainty of impunity coefficient's value in the penalty function [17] processing method, for all of the design constraints, each optimization solution must be either reasonable or unreasonable.

In the SPEA-RSVC-II, if solution x^1 dominates solution x^0, namely, x^1 is superior to x^0, it must meet either of the following conditions:

Solution x^1 meets the design requirements, but x^0 does not.

Neither of solution x^1 nor solution x^0 meets the design requirements, but the degree of meeting the design requirements for solution x^1 is better.

Both of solution x^1 and solution x^0 meets the design requirements, but solution x^1 dominates solution x^0.

The constraint dominant rule is taken as an independent model. It is used to judge the dominant relations among individuals. The SPEA-RSVC-II is applied to the multi-objective optimization problem of the injection molding machine. The improvements compared with the SPEA are shown as follows:

1. The Pareto-dominant conception is used to deal with the multiconstraints in the optimization problem. The design results are effectively limited within the scope, which is allowed by the engineering design.
2. The huge external population in the design problem is controlled into a certain magnitude by using the rough set-based support vector clustering method. It improves the computational efficiency and maintained the good border and distribution for the population.
3. The set-based priority selection method is applied to select the optimal solutions from the Pareto solution set. The uncertainty of artificial preferences is excluded.

The computational procedure of the SPEA-RSVC-II is shown as follows:

Step 1 Initialize this population;

Step 2 Delete the inferior individuals in the external population. Judge the number of individuals in the external population;

Step 3 Map the data sets to the high-dimensional feature space from X [18], then search the ultra-ball radius R which minimally envelopes the X point in the Hilbert space, ξ_i is the punishment item [19], namely:

$$\left\|\varphi\left(x^i - x^0\right)\right\|^2 \leq R^2 + \xi_i, \xi_i \geq 0 \tag{6}$$

Step 4 Take this point as the support vector border. Transform $\phi(x^i)$ to make one point on the surface of the feature space correspond.

Step 5 U is a finite non-empty set. R is the integral relation in the rough set theory [20]. The equivalent class of x^j is:

$$\overline{R}x^i = \left\{x^j \in U \middle| \left[x^j\right]_R \cap \left[x^i\right]_R \neq \phi\right\} \tag{7}$$

Step 6 The value is usually smaller than the maximum number of the individuals in the external population;

Step 7 Compute the fitness of external and internal population.

Step 8 The individual with bigger satisfaction degree will be selected in order to complete the goal of combining the external and internal population.

Step 9 Run the crossover and mutation operations of the algorithm [21].

Step 10 Check the maximum generation number. Judge whether the iteration operation is complete or not.

4 Optimal design of injection molding machine

4.1 Optimization model

The triple-objective optimization model with the largest mould moving speed and injecting pressure and the smallest injecting power is expressed as follows [22]:

Model:

Objectives $\max F = [Q, p_i, -N_i]$;

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
D_s	h_3	n	θ	η_1	η_2	δ	e	L_3	q_L	F_0	D_0	F_s	p_0	v_i	N
4.2	0.21	250	16	23.6	23.6	0.3	1.2	50	120	65	4.5	50	30	5	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	
6.0	0.28	300	19	52.3	52.3	0.5	2.5	75	500	102	5.6	110	150	10	1

Fig. 2 Chromosome coding

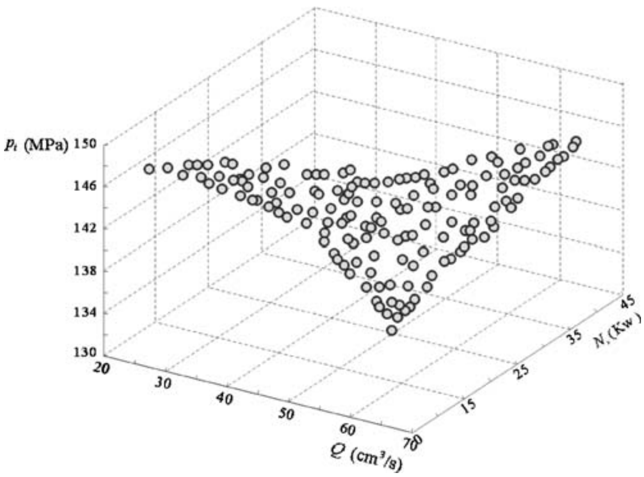

Fig. 3 Triple-objective optimization Pareto frontier

Constraints $\begin{cases} e_i(x) = 0, i = 1, \ldots, p; \\ n_j(x) \geq 0, i = 1, \ldots, q \, . \\ a_k(x) \in I, i = 1, \ldots, s \end{cases}$

Design parameters $x_n^{\min} \geq x_n \geq x_n^{\min}, l = 1, 2, \ldots, 18, \; N = 1, 2.$

$$X_m = [D_s, H_3, n, \theta, \eta_1, \eta_2, \delta, L_3, q_L, F_0, D_0, P_0, N]$$
$$X_n = [D_s, H_3, n, \theta, \eta_1, \eta_2, \delta, L_3, q_L, F_0, D_0, F_s, P_0, N, v_i].$$

In the above expressions, p is the number of equation constraints; q is the number of inequality constraints and a is the number of range constraints;

4.2 Chromosome coding

The value of N is suitable to be coded with binary. The values of P_0 and v_i is continuous within a specified scope. They are suitable to be coded with float. They are shown as Fig. 2.

The variation scopes of each design parameters are determined. The 16th bit represents the number of injection tanks. It is coded with one-bit binary. 0 represents N=1 and 1 represents N=2. The binary crossover and mutation rules are used. The design parameters from the first bit to the 15th bit varies continuously within their corresponding scope, the value of the initial population can be random. Then the binary crossover and mutation method is used.

4.3 Experiment of triple-objective model

In the design process of the HT1600X1N injection molding machine, SPEA-RSVC-II was implemented with C# program language to optimize the HT1600X1N injection molding machine's overall performance, and then, it was run in the personal computer with P4 2.6 GHz CPU, 512 M memory, and 120-G hard disk. The internal population, external population, and generation number of the triple-objective optimization model are, respectively, 250, 90, and 300; and the internal population, external population, and generation number of the triple-objective optimization model are, respectively, 600, 250, and 1000; through the test, set the float crossover probability as 0.65, set the float mutation probability as 0.2, set the distribution index of the crossover and mutation operations as 18, set the binary crossover as 0.2, and set the mutation probabilities as 0.7.

The parameter settings:

Lead angle $16 \leq \theta \leq 19°$;

The effective viscosity of the melting materials in the screw channel:

$23.6 \leq \eta_1 \leq 52.3$ Pa s;

Effective viscosity $22.6 \leq \eta_3 \leq 61.3$ Pa s;

Table 2 Results of optimal design

Individuals	Q	p_i	N_i	Individuals	Q	p_i	N_i
1	68.3	134.5	25.6	2	67.6	134.8	25.7
3	59.2	135.8	25.8	4	63.2	136.0	26.2
5	56.3	135.6	26.3	6	53.2	136.5	27.9
7	46.5	137.8	28.4	8	25.6	138.1	28.9
9	22.8	140.2	32.1	10	22.8	140.9	30.1
11	44.2	136.5	27.6	12	36.9	135.8	27.6
13	44.6	136.8	27.7	14	35.6	136.9	28.5
15	27.9	138.5	28.7	16	27.8	138.9	30.9
17	28.3	137.6	28.3	18	28.1	137.4	30.4
19	28.9	137.5	28.3	20	27.6	138.0	31.1
21	30.5	136.8	28.0	22	35.8	136.9	29.9
23	35.6	135.6	27.3	24	35.9	136.8	29.9
25	21.9	139.8	29.6	26	22.3	140.9	32.8
27	22.9	141.3	31.2	28	25.6	143.9	33.3
29	22.5	141.6	32.1	30	24.6	144.0	33.6

Diameter of screw stem	$5.2 \leq D_s \leq 6.0$ cm;
Depth of the screw channel's measurable section	$0.22 \leq h_3 \leq 0.30$ cm;
Length of the measurable section	$60 \leq L_3 \leq 80$ cm;
Rotating speed of the screw stem	$280 \leq n \leq 320$ r/m;
Machine barrel	$0.3 \leq \delta \leq 0.5$ cm;
Injection tank	N=1,2;
Injecting speed	$8 \leq v_i \leq 12$ cm^3/s;
Axial width of the screw stem	$1.5 \leq e \leq 2.8$ cm;
Piston of the injection tank	$67 \leq F_0 \leq 213$ cm^2;
Working oil pressure	$30 \leq p_0 \leq 150$ MPa;
Inner diameter of the injection tank	$4.5 \leq D_0$ 5.6 cm;
Cross-sectional area of the screw stem	$70 \leq F_s \leq 150$ cm^2.

The SPEA-RSVC-II is applied to optimize the HT1600X1N injection molding machine's design. The Pareto frontier with 60 individuals is shown as Fig. 3, and also, according to the set theory-based priority selection mechanism, the Pareto optimal solution is determined objectively. From the figure, it seems that when the injecting power is constant. Moreover, the design results simultaneously meet the design constraints of the plasticizing capacity and injecting pressure and injecting power. Therefore, the SPEA-RSVC-II which is applied to the triple-objective optimization design problem of the HT1600X1N injection molding machine's design can also get the Pareto frontier with uniform distribution.

The results are shown as Table 2.

5 Performance analyses

The comparison of the optimization design results of the HT1600X1N injection molding machine achieved by the

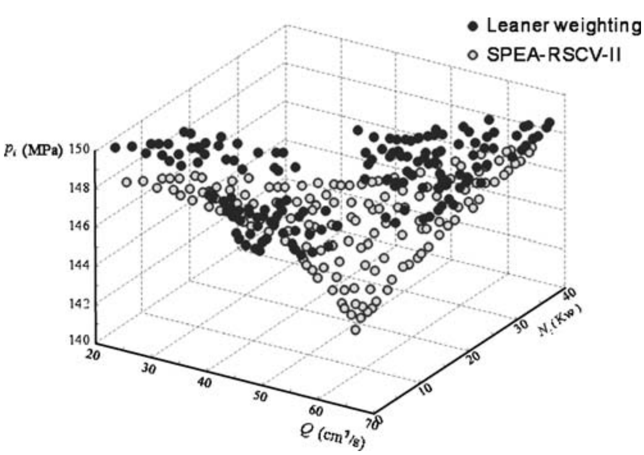

Fig. 4 Results of traditional linear weighting method and SPEA-RSVC-II

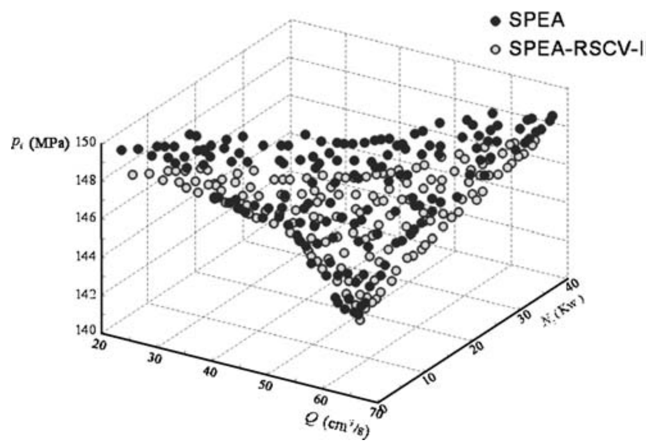

Fig. 5 Results of SPEA and SPEA-RSVC-II

traditional linear weighting method and the SPEA-RSVC-II are shown as Fig. 4, and also, the product design parameters and the corresponding objective function values when the objective Q is optimal and when the objective p_i is optimal are listed in Fig. 4. In Fig. 4, it can be seen that the SPEA-RSVC-II can get better Pareto frontier with good distribution and border in one single run than the linear weighting method in 60 runs.

In the solution solving process of the optimization design problem of the HT1600X1N injection molding machine's design, the SPEA-RSVC-II and SPEA are, respectively, applied. For the triple-objective optimization model, the optimization design Pareto frontiers achieved by these two algorithms are shown in Fig. 5.

Ten groups of experiments with different population size and generation number are conducted, and every group of experiment which in the same condition of population size and generation number are conducted 20 times, and the average time consumption is shown as Table 3. From the analysis of the data in Table 3, it can be seen that for triple-objective optimization model, the SPEA-RSVC-II costs 35.13% less time than the SPEA.

Compared with the SPEA, SPEA-RSVC-II, the time consumption can be shortened more greatly with the increase of the problem's scale.

Table 3 Experiment result analysis

Algorithm	Case 1 N=200; M=50; G=400;	Case 2 N=400; M=100; G=800;	Case 3 N=800; M=200; G=1200;
SPEA	1,023.44	2,156.87	5,125.12
SPEA-RSVC-II	792.96	1,504.63	3,119.66
Percent of time shortening (%)	22.52	30.24	39.13

6 Conclusions

The optimization design of injection molding machine is a complex multi-objective optimization problem with constraints. There is large external population in the optimization design project. The traditional linear weighting method, SPEA, and the SPEA-RSVC-II are, respectively, applied to the optimization design problem of the HT1600X1N injection molding machine's overall performance. The set-based support vector clustering method can effectively accelerate the clustering operations of the large-scale population. So the computing efficiency is improved significantly. The optimization results of the application example have proved that the SPEA-RSVC-II is able to solve the multi-objective optimization design problem of the injection molding machine effectively compared with traditional linear weighting method and SPEA.

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