Multi-objective optimization design of passive filter based on particle swarm optimization

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Abstract. Using particle swarm optimization algorithm, aiming at the investment cost, filtering effect and reactive power compensation ability of passive filter, the weight of each objective function is determined according to the dispersion order method, and the passive filter is designed by multi-objective optimization. In addition, the actual calculation is carried out by taking the power grid parameters of the self-elevating and self-propelled petroleum engineering ship of “Feng Long 01” as an example. Further, a ship power grid simulation model is built under the Matlab/Simulink environment to verify the practicality of the optimized passive filter design.

1. Introduction
In an electric propulsion ship, the electric energy consumed by the electric motor accounts for most of the electric power generation. However, the main propulsion motor is generally operated by the frequency converter, and the AC/DC converter of the inverter will draw reactive power from the grid and inject a large amount of harmonic current, resulting in the electric power propulsion ship power grid is more prone to harmonic pollution and power. Problems such as low factors have a serious impact on the power quality of shipbuilding grids. If the corresponding improvement measures are not taken, it may seriously affect the safe and economic operation of the ship [1].

In order to solve the problem of harmonic pollution of electric propulsion ship, this paper introduces particle swarm optimization algorithm to optimize multi-objective parameters of passive filter (PPF). By setting the investment cost, filtering effect and reactive power compensation capability of the passive filter as the optimization target, a passive filter design method with better comprehensive performance will be obtained.

2. The analysis of passive filter optimization target

2.1. The principles of design
The passive filter is a power filter device with only three parameters (resistance, capacitance and inductance), but its design must consider many factors, such as economy, safety, filtering effect and reactive power compensation. The parametric design of the passive filter is a typical nonlinear multi-
objective optimization problem. The design principle and multiple design goals of the passive filter should be considered in the design.

Combining the various methods and ideas of passive filter design, it can be concluded that design of passive filters generally meets the following principles [2, 3].

1) Single-tuned filter capacitors and inductors must meet the requirement of the resonant frequency, and high-pass filter capacitors and inductors must meet the requirement of the cutoff frequency.

2) After the installation of the passive filter, the harmonic content of the power grid should meet the relevant requirements. For the ship power grid, the voltage distortion rate is less than 5% to meet the requirements of the Steel Ship Classification Rules.

3) The added passive filter should consider the need of reactive power compensation, which make the power factor as close as possible to 1.

4) The installed passive filter, it cannot be connected in series or parallel with the inductance and capacitance of the power grid.

5) Each filter circuit must consider not only the harmonics but also the added background harmonic content.

2.2. The mathematical description of optimization goal.

According to the above objective optimization principle, considering the various factors, the investment cost, filtering effect and reactive power compensation capability of the passive filter are selected as the optimization objectives. The mathematical descriptions are as follows.

(1) Minimum investment cost

Assume that the unit price of the filter resistor, capacitor, and inductor are \(k_1\), \(k_2\), \(k_3\). The initial investment cost of a passive filter bank can be expressed as

\[
\min F_1 \quad F_1 = \sum_{i=1}^{m} (k_1 R_i + k_2 C_i + k_3 L_i)
\]

Where \(m\) is the number of filter banks. The passive filter designed in this paper has 4 groups, which are 5, 7 and 11 single-tuned filers and a set of high-pass filters, respectively. After inquiry, the unit prices of resistance, capacitance and inductance are \(k_1=4.4¥/Ω\), \(k_2=32¥/uF\), \(k_3=16¥/mH\)

(2) The best filtering effect

The filtering effect of the passive filter can be measured by the total distortion of the current harmonics after the addition of the passive filter. The total distortion of the harmonics after adding is

\[
\min F_2 \quad F_2 = THD_i = \sqrt{\frac{\sum I_n^2}{I_1}} \times 100\%
\]

Where \(I_1\) is the rms value of the fundamental current, \(n\) is the highest number of harmonic calculations. In order to simplify the calculation, \(n\) is 20 in this paper.

(3) Optimal reactive power compensation

In terms of reactive power compensation, it is hoped that the passive filter can satisfy the reactive power compensation requirement of the system as much as possible without over-compensation. Assume that the total reactive power compensation of the filter is \(Q_n\), the filter reactive power compensation effect can be expressed as:

\[
\min F_3 \quad F_3 = C - Q_n
\]
Where $C$ is a larger positive number, which can guarantee the $C - \bar{Q}_n$ is greater than 0.

3. Multi-objective optimization design of passive filter based on improved particle swarm optimization

3.1. Particle swarm optimization

Particle swarm optimization is an intelligent algorithm proposed in 1995 based on the study of group behavioural processes such as migratory bird population migration and foraging. Because of its simple principle, convenient implementation and good convergence effect, it is widely used in solving complex multi-objective optimization problems [4].

The basic idea of particle swarm optimization is to abstract the individual birds in the flock into individual particles. The movement of the individual birds is abstracted into the movement of the individual particles. The group migration and foraging behaviour of the flock are abstracted into changes, which is the process of finding the optimal solution. The migration and foraging behaviour of flocks is simulated. The initial particle swarm is composed of $M$ individuals, each of which has a random position $X$, and the $X$ has $N$ dimensions according to the number of variables, which is $X_i = (x_{i1}, x_{i2}, x_{i3}, ..., x_{iN})$. The velocity of the particle is expressed as $V = (v_{i1}, v_{i2}, v_{i3}, ..., v_{iN})$. Since the flock moves to the first bird near the migratory site and food during migration and foraging, each particle preserves the optimal location (solution) $P_{best}$ currently found by the particle swarm. Meanwhile, the historical best position $P_{best}$ of the particle itself will also affect the motion of the particle.

The speed and position change of each iteration of the particle is

$$V_{i}^{k+1} = wV_{i}^{k} + c_1r_1(P_{best} - x_i) + c_2r_2(G_{best} - x_i)$$  \hspace{1cm} (4)

$$X_{i}^{k+1} = X_{i}^{k} + V_{i}^{k+1}$$ \hspace{1cm} (5)

Where $c_1$, $c_2$ is called the learning factor of particle. $r_1$ and $r_2$ is a random value between 0 and 1. The velocity of a particle consists of three parts. The $wV_{i}$ is the influence of particles on their own inertia, reflecting the pursuit of particles in the direction of their own movement. $c_1r_1(P_{best} - x_i)$ is the continuous learning process of particles that are influenced by their own historical experience, reflecting the best position of the particles. $c_2r_2(G_{best} - x_i)$ is the particle which is affected by the experience of the population, reflecting the social learning of the particle. The three parts work together to ensure that the particle group moves in the direction of the optimal solution. The interaction effect is shown in Figure 1.
In the particle swarm optimization algorithm, the size of the inertia weight parameter directly affects the global search ability and local convergence ability of the particle swarm. In order to make the algorithm have better global search ability in the early stage, it can better converge to the optimal value in the later stage and obtain the exact solution. In this paper, a linear differential decrement inertia weighting strategy was chosen. The corresponding inertia weight calculation formula is

$$w(t) = w_{\text{start}} - \frac{(w_{\text{start}} - w_{\text{end}})}{t_{\text{max}} - t} 	imes t^2$$

(6)

Where $w_{\text{start}}$, $w_{\text{end}}$ is maximum and minimum values for the set inertia weight. In this paper, $w_{\text{start}} = 0.9$, and $w_{\text{end}} = 0.2$. $t$, $t_{\text{max}}$ is number of current iterations and the maximum number of iterations set, respectively. Using the inertia weight of the linear differential decrement of the above formula, the particle swarm algorithm has a larger inertia weight in the early stage and a relatively slower decrease, which can make the algorithm find the possible optimal solution in the global as much as possible. In the later stage of the algorithm, the inertia weight The speed of the reduction is getting faster and faster. Once the particle finds the proper solution, it can guarantee the fast convergence ability and obtain the accurate optimal solution.

3.2. The extraction of target function

In order to optimize the investment cost, filtering effect and reactive power compensation capability of the passive filter at the same time, the objective function is set as follows

$$F = \lambda_1 \left( \frac{F_1 - \min F_1}{\max F_1 - \min F_1} \right) + \lambda_2 \left( \frac{F_2 - \min F_2}{\max F_2 - \min F_2} \right) + \lambda_3 \left( \frac{F_3 - \min F_3}{\max F_3 - \min F_3} \right)$$

(7)

Where, $\max F_1$, $\max F_2$ and $\max F_3$ is the maximum value obtained by single-objective optimization for the single objective functions $F_1$, $F_2$ and $F_3$ respectively. $\min F_1$, $\min F_2$ and $\min F_3$ is the minimum value obtained by single-objective optimization functions $F_1$, $F_2$ and $F_3$. $\lambda_1$, $\lambda_2$, $\lambda_3$ and $\lambda_4$ is the weights for the three single objective functions respectively, and $\lambda_1 + \lambda_2 + \lambda_3 = 1$.

In the multi-objective optimization of the passive filter, $F$ is taken as the objective function, and the constraint is expressed as a penalty function as the objective function. By changing the values of
and $\lambda_3$, the investment cost, filtering effect and reactive power compensation of the passive filter with different emphasis.

Considering that there may be multiple single-objective functions that are determined by the same set of variables, the results between these single-objective functions are influential with each other. Therefore, this paper uses the dispersion order method to quantitatively calculate the weight of each single target. The calculation steps of the dispersion sorting method are as follows [5]

1) Finding the optimal solution corresponding to the optimal point of the single objective function.
2) The obtained optimal solutions are respectively brought into a single objective function, and the function values corresponding to each objective function are obtained.
3) Calculating the dispersion of each single objective function, and obtaining the dispersion of the function value and the optimal function value when each single objective function takes the other single objective optimal solution respectively.
4) Calculating the mean deviation of each single objective function.
5) Calculating the weight of each single objective function.
6) The range of the solution set of each single objective function is equalized, and the weights are reordered according to the mean value of the dispersion of the single objective function, and the small mean value of the large mean deviation is small, and the large mean value of the deviation is small.

3.3. Experimental results

In order to verify the proposed method in this paper, the example calculation is carried out with reference to the power grid parameters of the self-propelled petroleum engineering ship of Fenglong 01.

![Figure 2. "Fenglong 01" self-lifting self-propelled petroleum engineering ship](image)

The length of the ship is 65m, the width is 41m, and the depth is 5m, and it is equipped with 3 generators, each with a power of 1100kW. The ship’s grid voltage is 690V (single-phase RMS) and the frequency is 50Hz. When the propulsion motor is working at rated power, the fundamental current reaches the maximum value of 1150A (single-phase RMS). The actual ship measurement data is shown in Table 1. The distortion rate was 33.08%.
Table 1. Grid fundamental/harmonic current information

| Fundamental/harmonic times | Electric current(A) | Percentage(%) |
|----------------------------|---------------------|---------------|
| 1                          | 1150                | 100.0         |
| 5                          | 361.45              | 31.4          |
| 7                          | 26.70               | 2.3           |
| 11                         | 96.82               | 8.4           |
| 13                         | 29.81               | 2.6           |
| 17                         | 51.57               | 4.5           |
| 19                         | 20.43               | 1.8           |

The process of calculating the weight of each single objective function using dispersion order method is shown in Table 2.

Table 2. Maximum and minimum of single objective function and optimal solution

| Parameters | \( F_1 \) | \( F_2 \) | \( F_3 \) |
|------------|-----------|-----------|-----------|
| max        | 595240.94 | 3.90      | 9847664.42|
| min        | 236944.90 | 1.80      | 9618708.10|
| \( x^j(j=1,2,3) \) | [7.16E+02, 4.56E+01, 1.34E+02, 9.13E+01] | [1.52E+03, 1.20E+02, 4.10E+02, 4.30E+02] |

Table 3. The fitness value of a single objective function for each optimal solution

| Optimal solution | \( F_1 \) | \( F_2 \) | \( F_3 \) |
|------------------|-----------|-----------|-----------|
| \( x^1 \)       | \( * \)   | 3.90      | 9618708.10|
| \( x^2 \)       | 595239.20 | \( * \)   | 9847664.42|
| \( x^3 \)       | 595239.20 | 1.80      | \( * \)   |

Table 4. The calculation of objective function

| Optimal solution | \( \frac{F_1 - \min F_1}{\max F_1 - \min F_1} \) | \( \frac{F_2 - \min F_2}{\max F_2 - \min F_2} \) | \( \frac{F_3 - \min F_3}{\max F_3 - \min F_3} \) |
|------------------|------------------------------------------|------------------------------------------|------------------------------------------|
| \( x^1 \)       | 1.00                                     | 0                                        | 1.00                                     |
| \( x^2 \)       | 1.00                                     | 0                                        | 0                                        |
| \( x^3 \)       | 1.00                                     | 0                                        | 0                                        |
| Mean value of dispersion | 1.00                                   | 0                                        | 0                                        |
| \( \Sigma \delta \) | 2.00                                   |                                           |                                           |
| Target weight   | 0.5                                      | 0.25                                     | 0.25                                     |

From the calculation results, \( \lambda_1 = 0.5 \), \( \lambda_2 = 0.25 \), \( \lambda_3 = 0.25 \), and \( \lambda_1 + \lambda_2 + \lambda_3 = 1 \). The process of setting the weights according to the calculation result and using the particle swarm algorithm for multi-objective optimization is as shown in Fig. 3.
The calculation results are compared with the traditional empirical methods (minimum capacitance and reactive power compensation method [6, 7]), as shown in Table 5.

**Table 5. The parameters of passive filter**

| Filter         | PSO optimization     | Minimum capacitance method | Reactive compensation method |
|----------------|----------------------|-----------------------------|------------------------------|
| 5th filter     | C=716.34 μF          | C=716.24 μF                 | C=1.52 mF                   |
|                | L=0.5663 mH          | L=0.5664 mH                 | L=266.91 μH                 |
|                | R=0.0178 Ω           | R=0.0178 Ω                 | R=0.0084 Ω                 |
|                | C=60.18 μF           | C=45.63 μF                 | C=0.12 mF                  |
| 7th filter     | L=3.4394 mH          | L=4.5360 mH                 | L=1831.75 μH                |
|                | R=0.1512 Ω           | R=0.1994 Ω                 | R=0.0805 Ω                 |
|                | C=133.80 μF          | C=133.62 μF                 | C=0.41 mF                  |
| 11th filter    | L=0.6265 mH          | L=0.6273 mH                 | L=205.45 μH                 |
|                | R=0.0433 Ω           | R=0.0433 Ω                 | R=0.0142 Ω                 |
|                | C=429.87 μF          | C=91.33 μF                  | C=0.43 mF                  |
| High-pass filter | L=0.0698 mH         | L=0.3280 mH                 | L=69.69 μH                  |
|                | R=0.5699 Ω           | R=2.6800 Ω                 | R=0.57 Ω                   |

Multi-objective design results in filter parameters compared to traditional empirical methods is shown in Table 6.
Table 6. Comparison of different methods for designing passive filters

| Method                  | Cost  | Current distortion rate (%) | Reactive power compensation capacity (kvar) |
|------------------------|-------|-----------------------------|--------------------------------------------|
| Minimum capacitance method | 23.7  | 3.90                        | 152.34                                     |
| Reactive compensation method | 59.5  | 1.80                        | 381.29                                     |
| PSO optimization        | 32.2  | 2.08                        | 205.81                                     |

It can be seen from Table 6 that the initial investment cost of the minimum capacitance method is the least, only ¥237,000, but its filtering effect and reactive power compensation ability are relatively poor. The reactive power compensation method selects a large capacitor, its filtering effect and reactive power compensation capability are excellent, but the cost increases significantly. Compared to the above two traditional method, the particle swarm multi-objective optimization method takes into account the cost, filtering effect and reactive power compensation, and the filter effect (increased by 46.7%) and reactive power in the case of less initial investment cost (increased 85000, accounting for 35.9% of the initial investment), and the compensation capacity (up 35.1%) has been greatly improved.

3.4. Simulation verification
In order to verify the correctness of the optimization results, the simulation model is built in Matlab/Simulink according to the ship's power grid parameters. As shown in Figure 4, the same harmonic content as the actual ship is set.

![Figure 4. Ship grid simulation model](image)

Before filtering, the active power of system is 1072, reactive power is 796, and power factor is 0.8. The results of each harmonic content are shown in Fig.5. The total distortion of the harmonic current is 33.08%, which is the same as the actual ship parameters.
Figure 5. The harmonic content before filter

The filter designed by the minimum capacitance method is put into the model, the power factor change is 0.9, the reactive power is compensated to some extent, and the current waveform of the A phase after filtering is shown in Fig. 6. The total distortion rate of the harmonic current is reduced to 3.74%. At this time, the initial investment cost was ¥237,000.

Figure 6. A-phase current waveform after minimum capacitance method filtering

The filter designed by reactive power compensation method is put into the model, the power factor change is 0.98, the reactive power is better compensated, and the current waveform of the filtered A phase is shown in Figure 7. The total distortion current of the harmonic current is reduced to 1.71%, the initial investment cost was ¥595,000.
The filter of the particle swarm optimization design is put into the model, the power factor change is 0.93, and the current waveform of the A phase after filtering is as shown in Fig. 8. The total distortion rate of the harmonic current is reduced to 2.05%. ¥322,000.

Figure 7. A-phase current waveform after filtering by reactive power compensation capacity method

Figure 8. A-phase current waveform after filtering by particle swarm optimization filter

The simulation results are basically consistent with the multi-objective optimization calculation results. Compared with the minimum capacitance method, the optimization algorithm has a significant improvement on the filtering effect and reactive power compensation based on the initial investment of the appropriate amount, which is greatly reduced compared with the reactive power compensation
method. With the investment cost, it can be concluded that the obtained results by multi-objective optimization are accurate.

4. Conclusion

(1) By setting the investment cost, filtering effect and reactive power compensation capability of the passive filter as the optimization target, the multi-objective optimization design of the relevant parameters of the passive filter is carried out. Among them, the weighting of each optimization single target is determined by using the dispersion order method.

(2) The ship network simulation model is built in the Matlab/Simulink environment to verify the effectiveness of the example calculation results.

(3) There are many similar cluster intelligent optimization algorithms, such as genetic algorithm. Only particle swarm optimization algorithm is selected in this paper. A comparative study of related algorithms and a better design approach are the focus of further research.

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