The design of AGV’s dynamic wireless power transmission power supply based on Adaptive Weight Value Multi-objective Genetic Algorithm

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Abstract. AGV is the application of modern factory intelligence and automation. With the development of wireless power transmission (WPT), its transmission efficiency and stability are getting higher and higher. However, from static charging to dynamic power supply, the cost of technology implementation has increased significantly. This paper proposed a method to supply power to logistics AGV by intermittent segment, established the binary coverage model according to the power coverage distance, and designed an Adaptive Weight Value Multi-objective Genetic Algorithm (AWMOGA) for this model to Optimizing the path design of sectional power supply. The influence of three weight value adaptive methods on the optimization results is analyzed, the effectiveness of the proposed method is analyzed and verified through case simulation.

1. Introduction
Wireless power transmission (WPT) developed rapidly, especially the Continuous improvement of coupled magnetic resonant wireless power transmission technology, the application of wireless power transmission in static charging and dynamic power supply of power system is increasing[1-4]. Dynamic wireless power transmission (DWPT) can be divided into long guide rail type and section type according to different design methods of transmitting coil[5-6]. WANG H[7] proposed a non-contact power supply system by combining power supply cabinet and AGV, the use of on-board batteries is abandoned, its belonging to the category of long track dynamic charging. YANG W[8] designed a power supply loop system according to the demand of power, it can meet the multi-station AGVs simultaneously. The relay method of segmental dynamic wireless charging is studied by ZHAO J[9-10], accurate positioning of primary coil and local power supply are realized during dynamic charging.

In this paper, an intermittent segmental AGV power supply system is proposed, and the AGV’s total driving path is divided into charging section and non-charging section, separate charging sections into the overall driving path. In this way, the car needs a very small battery capacity to ensure its stable operation. Because of the decentralized design of charging sections, reasonable distribution of charging sections and non-charging sections can greatly reduce the cost of charging systems. It provides a new idea and solution for the dynamic charging design of AGV.
2. Description of optimal configuration of intermittent segmented power supply path

In view of improving dynamic wireless power transmission efficiency and reducing system application cost, the intermittent segmented charging system structure is shown in Fig.1. In this structure, the charging section and non-charging section are staggered. The charging path system structure shown in figure 1 is composed of two charging sections with different power. The core of the design of intermittent segmented power supply system is to determine the optimal number and location of charging sections [11].

In this paper, a mathematical model based on power coverage distance is established for the reasonable distribution of sections. And proposed an Adaptive Weight Value Multi-objective Genetic Algorithm (AWVMOGA) for this model to Optimizing the number of charging sections and the location of each section to achieve the maximum power coverage area and the minimum cost.

3. Mathematical model of the optimal configuration of intermittent segmented power supply path

3.1. Forward binary coverage model

We just consider the power coverage range of the forward direction, and established the forward binary coverage model to describe the segment configuration. Suppose the charging section $M_s$ of type $s$ is laid at the location of $L_{is}$, the forward distance between the arbitrarily separated small segment ($L_j$) and the charging section can be expressed in formula (1):

$$d(M_{is}, n) = L_j - L_{is} \quad (j > i > 0) \quad (1)$$

The power coverage probability of this charging section $M_{is}$ for any small segment in the total path is:

$$p(M_{is}, N) = \begin{cases} 1, & 0 \leq d(M_{is}, n) \leq R_s \\ 0, & d(M_{is}, n) > R_s \text{ or } d(M_{is}, n) < 0 \end{cases} \quad (2)$$

The same small segment also has the chance to be covered by multiple charging sections at the same time. The event of any small segment $n$ being coordinated by multiple charging sections is defined as $C_k$

$$p(C_k) = 1 - \prod_{i=1, s=1}^{N, S} [1 - p(C_{iks})] \cdot M_{is} \quad (3)$$

The coverage of the forward running total path can be defined in formula (4). Where $L$ is the length of the total path.

$$P_f = \sum_{k=1}^{N} (p(C_k)) / L \quad (4)$$

3.2. Bidirectional binary coverage model

In the reverse operation model, the power coverage probability $p'(M_{is}, N)$ of the charging segment $M_{is}$
for any small segment in the total path is the same as that of the forward binary coverage model. The calculation of the probability \( p'(C'_k) \) of the co-coverage event \( C'_k \) of any small segment \( n \) by multiple charging sections is also the same as above.

According to the different AGV requirements in different regions of the manufacturing plant, the charging section coverage density in places where there is more demand is large, and the charging section coverage density in places where there is less demand should also be reduced accordingly. Set the coverage probability threshold of any small segment \( n \) as \( p_n \) and use \( r(p_n) \) to indicate whether the small segment \( n \) meets the coverage probability requirement, then there is:

\[
 r(p_n) = \begin{cases} 
 1 & p(C_n) + p'(C'_n) \geq p_n \\
 0 & \text{otherwise} 
\end{cases} \quad (5)
\]

The bidirectional coverage probability \( P \) of the total path is defined as:

\[
 P = \sum_{k=1}^{N} \left( \frac{r(p_k)}{L} / L \right) \quad (6)
\]

### 3.3. Mathematical model of optimal configuration

The AGV intermittent segmented DWPT power supply design criterion is to achieve the maximum power coverage distance to the total path and the minimum economic cost, which is a typical double-standard design problem. The two objectives in the optimization configuration are in conflict, so the only solution to the problem cannot be obtained, we can only try to find the pareto optimal solution\([12-13]\). The economic cost of charging section of s-type is set as \( e_s \), and the objective function of optimal configuration model is defined as follows.

\[
 \max F(\xi) = \left\{ \sum_{\xi=1}^{N} \frac{r(p_{\xi})}{L} / L, \sum_{\xi=1}^{N} \sum_{s=1}^{S} e_s M_{\xi s} \right\} \quad (7)
\]

The maximum objective function value \( \max F(\tau) \) can not only guarantee the coverage probability of the charging section configuration to the AGV trolley's total running path, but also minimize the economic cost.

### 4. The design of intermittent segmented DWPT power supply based on AWVMOGA

Genetic algorithms initially initialize a set of random solutions as genetic "populations"\([14-15]\), Each solution as an individual, simulates the selective genetic mechanism in nature to search for the optimal solution iteratively. The solution is evaluated by the individual adaptive value, and the individuals with higher fitness have higher selectivity. The offspring population is produced by the selection of the adaptive value after crossing and variation, until the global optimal solution is found. The traditional genetic algorithm is improved in this paper, make it more suitable to multi-objective optimization model. The optimal solution to the intermittent segmented DWPT design problem can be quickly found.

#### 4.1. Chromosome coding and population initialization

According to the characteristics of this model, every set of chromosomes is coded in real Numbers to describe any feasible solution, so as to guarantee the ergodicity and randomness of the solution range\([16]\). After the total path is discretized into \( N \) small segments with length 1, the regulation "0" refers to the section where no charge is laid, and non-0 real number refers to the section where charge is laid. Figure 2 shows the chromosome formed by the encoding of a feasible solution, the algorithm starts with a random number of feasible solutions as the initial population for subsequent work.

![Figure 2. The chromosome formed after the feasible solution is encoded](image-url)
4.2. Fitness function

After the analysis of the binary coverage model, the optimal allocation objective function is composed of two sub-objective functions: coverage rate and economic cost, and the two sub-goals interact with each other. As the population iterates, it is necessary to find an optimal balance in the development of this conflict. Now we add different coefficients \( w_1 \) and \( w_2 \) to the two sub-objective functions, the total objective function is the weighted sum of the normalized transformations of the two sub-objectives. Defined as follows:

\[
F(\xi) = w_1 \cdot \sum_{\xi=1}^{N} \left( r(p_{\xi}) \right) / L + w_2 \cdot \sum_{\xi=1}^{N} \sum_{s=1}^{S} e_s M_{\xi s}
\]  

(Eq. 8)

The selection of the weights \( w_1 \) and \( w_2 \) determines the fitness function. \( w_1 \) mainly affects the coverage probability of the total path. \( w_2 \) determines the economic cost, that is, the number of charging sections laid. According to empirical values, we usually take \( w_1 = 0.9 \), \( w_2 = 0.1 \)\(^{[17]}\). However, the result is not the optimal solution when applied to the binary coverage model established above. In this paper, a weight value method based on adaptive mechanism is proposed. On the premise that \( w_1 + w_2 = 1 \), select the appropriate weight value according to the evolution progress of the algorithm. At the beginning of the algorithm iteration, given smaller \( w_1 \) and larger \( w_2 \). This enables the feasible solution to have a more balanced distribution in the global stage and better ergodicity in the initial stage. As the number of iterations increases, \( w_1 \) gradually increases and the value of \( w_2 \) decreases accordingly. In the later stage of the algorithm, the larger \( w_1 \) can guarantee the maximum coverage of the total path, and the smaller \( w_2 \) can reduce the economic cost.

The weight \( w_1 \) change of the whole algorithm period can be depicted by a monotone increasing function. Monotone increasing functions include linear function, concave function and convex function. As shown in figure 3, three types of monotonic increasing functions are designed according to literature \([18]\).

![Figure 3. Three weight change curves](image)

There, \( w_{min} \) is the minimum value of the weight \( w_1 \), \( w_{max} \) is the maximum value of the weight \( w_1 \), \( t \) is the current number of iterations, and \( T \) is the maximum number of iterations. In the next section, the effects of these three weight change functions on pareto optimal solution for searching intermittent segmented DWPT power supply design by genetic algorithm are discussed in detail.

5. Simulation and analysis

In this paper, we used system simulation software to analyze the intermittent segmented DWPT power supply design. In the simulation, two power supply sections of different powers are laid to supply power to AGV cars in operation within the ring path with a total length of 50m. The running power of AGV car is 200W, and the specific parameters of power supply section are shown in table 1. The maximum iteration times of the improved genetic algorithm were set as \( T=300 \), \( w_{min}=0.26 \), and \( w_{max}=0.72 \). Three kinds of weight change functions selected in the third section are simulated and analyzed respectively.
Table 1. Power supply section parameter

| Type  | P_s/W | R_s/m | c_e/Yuan |
|-------|-------|-------|----------|
| type1 | 600   | 3     | 1200     |
| type2 | 1000  | 5     | 1800     |

Figure 4 shows the trend chart of the fitness function values of the four algorithms with the number of iterations. MOGA has the fastest convergence speed, but it is easy to get into the local optimum and cannot get the best pareto solution. The convergence speed of f1-AWVMOGA is lower than that of MOGA, and it will not get into the local optimum. The pareto solution obtained in the end is better than that of MOGA. f2-AWVMOGA has a slow convergence rate and will also fall into local optimum. The fitness function values of f3-AWVMOGA algorithm not only converges the slowest, but also declines in the middle. After analysis, the reason may be that the $w_1$ in the initial iteration of the algorithm is small. Meanwhile, the growth rate of $w_1$ was slow in the early stage and rapid growth in the later stage. As the result, the population in the early evolution period was slow and could not keep up with the change of $w_1$ value, and the population in the late evolution period moved towards the optimal individual sharply.

Figure 4. Four algorithm fitness function values

Figure 5 is the power supply path configuration diagram obtained in the iteration process of AWVMOGA algorithm when f3 weight change curve is used. With the iteration of the algorithm, the power supply path configuration tends to the optimal distribution, and the coverage gradually reaches 100%. The final optimal configuration distribution is, eight type1 power supply sections were used (The positions are 1, 9, 12, 14, 27, 31, 41, 47), and six type2 power supply sections were used (The positions are 4, 16, 23, 33, 37, 43).

Figure 5. Optimal power supply section configuration

6. Conclusion

In this paper, an intermittent segmented DWPT power supply mode is proposed for AGV system of intelligent manufacturing plant, and took its optimization design as the research target. According to the binary coverage model and economic cost, the mathematical model is established. The most important thing to know is how to use fewer power parts to ensure path coverage. An Adaptive Weight Value Multi-objective Genetic Algorithm (AWVMOGA) is designed for this binary model, and the influence of three weight curves on the algorithm is analyzed. Simulation analysis shows that
AWVMOGA algorithm is not easy to get into the local optimal solution when the weight value $w_1$ changes as a convex function, and can quickly find the optimal solution to ensure full path coverage and the best economic benefit. This provides a new idea for the design of manufacturing plant AGV power supply system, and has important theoretical and practical significance for the design of large-scale DWPT power supply system.

**Project:**
Tianjin science and technology project (18ZXZNGX00130)
Science and technology service project of state grid tianjin electric power company in 2019 (SGTJCN00YJJS1900527)

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