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Research Article

An Optimal Allocation Method of Power Multimodal Network Resources Based on NSGA-II

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Basic services for power business were provided by the power multimodel network providers. However, because the power multimodal network is usually complex and changeable, the service of power business is often unstable. This problem can be solved by a suitable network resource optimization method. Therefore, how to design a network resource optimization method that seeks a compromise between multiple performance indicators that achieve the normal operation of power multimode networks is still extremely challenging. An optimal allocation method of power multimodal network resources based on NSGA-II was proposed by this paper. Firstly, the power multimodal network-resource model is established, and the problems existing in the resource optimization process are analyzed. Secondly, preprocessing technology and indirect coding technology are applied to NSGA-II, which solves the coding problem and convergence problem of the application of genetic algorithm to the optimization of network resource allocation. Finally, the simulation results show that, compared with the control algorithm, this method has further optimized the various indicators of the resource allocation of the power multimodal network, and the performance has been improved by more than 6%.

1. Background

New business needs with large connections and wide coverage have gradually arisen by the research and development of power multimodal networks. However, the current power multimodal network is difficult to meet the business processing needs, which will result in a significant increase in network transmission pressure and computing load. In addition, in the power multimode network, the network structure is relatively complicated, many different types of communication equipment are needed, and the connection methods between the devices and the information conversion methods are different, resulting in the entire power multimode network [1]. The network structure is very complicated which causes the power multimodal network structure to become very complicated. At the same time, the power system is the infrastructure of daily life, which requires the power multimode network to have higher stability. Therefore, the power multimode network is also required to be in the process of working without various interruptions and sudden changes, which means higher flexibility and reliability.

Optimizing the software and hardware in the power multimodal network to improve the quality of service and meet the business needs is necessary to solve the above problems. At the software level, reasonable resource optimization can be performed on multiple indicators such as link delay, reliability, and resource occupancy distribution of the power multimodal network [2]. On the one hand, establishing a reasonable power multimodal network resource model is needed for common resource optimization methods, and on the other hand, reasonable optimization methods for different resource optimization scenarios are also needed.

Therefore, a suitable and reasonable power multimodal network resource model should be established firstly. Some existing model schemes only consider single indicators, such as delay and reliability [3], while others consider various network indicators comprehensively, but only part of the indicators can be optimized due to the limitation of optimization methods [4]. Secondly, choosing a reasonable method for the scene of the power multimodal network is necessary. Because network resource optimization is an NP-hard problem, heuristic algorithms are proposed to obtain approximate optimal solutions, but it is easy to fall into local optimal results. In addition, among the heuristic algorithms, some heuristic algorithms such as the ACS algorithm were originally designed for discrete problems and are not suitable for network resource optimization. The GA algorithm designed for continuous problems is considered an effective way to solve the problem of network resource optimization. Among them, the NSGA-II algorithm uses fast nondominated sorting with elite strategy, which solves the main shortcomings of NSGA and achieves fast and accurate search performance, so it is suitable for complex and multiobjective optimization problems [5].

In summary, in view of the above-mentioned resource optimization problem in the power multimodal network, this paper proposes a multimodal network resource optimization model and designs a power multimodal network resource optimization allocation method based on NSGA-II to optimize the model. The main contributions of this paper are listed as follows.

(1) From the perspective of resource association and business relevance, the indicators of resource expenditure, link reliability, resource occupancy, and distribution in the power multimode network are analyzed, and the power multimode network resource optimization model is designed to ensure service quality of the power multimode network

(2) Based on the NSGA-II algorithm, a power multimodal network resource optimization allocation method is designed and implemented to solve the resource optimization problem. By introducing indirect coding technology and preprocessing technology, the algorithm is guaranteed convergence speed while the network resources are optimized

The rest of this paper is organized as follows. Section 2 discusses the related work. Section 3 builds a power multimodal network optimization model. Section 4 proposes a multiobjective optimization method based on NSGA-II. Section 5 verifies the performance of the algorithm through simulation, and the last chapter summarizes the full text and draws conclusions.

2. Related Work

In this section, we focus on two important stages in the power multimode network, which are optimized allocation of network resources and multiobjective optimization.

2.1. Optimized Allocation of Network Resources. The optimization of network resource allocation is mainly at the software level by recontrolling and adjusting service paths in multimodal network logic resources to improve network resource utilization and reduce service response time, so as to meet the service quality of various power services. Reference [6] proposes an entropy-based business uniform distribution algorithm, which analyzes business traffic according to the business characteristics of the power communication network. The distribution of business traffic reflects the operating status of the network business, and the business information entropy is used as a measure of the uniformity of network business distribution. Then, use the information entropy as the objective function to get the algorithm for optimizing global business routing. Reference [7] proposes a hierarchical QoS routing method based on network resource reservation by calculating the required routing and determining the allocation sequence of the link resources to be reserved, thereby minimizing the response time. Reference [8] discusses the online convex optimization problem including the adversarial loss function and adversarial constraints and proposes an improved online saddle point (MOSP) method and applies it to the dynamic network resource allocation problem. Reference [9] proposed an integrated analytic hierarchy process (IAHP), which established an optimization model under the premise of considering factors such as resource cost, connectivity, and reliability, to obtain a relatively balanced solution under the condition of satisfying constraints.

In short, the current solutions for network resource optimization are mostly focused on optimizing network service paths, which means changing routing options through different methods to ensure network service quality. However, the optimization results of the above methods are relatively simple, which lack consideration of power multimodal network scenarios. Moreover, the optimization measures of some methods are often fixed when the network is initialized, and there is no suitable solution to the problem of dynamic network resource allocation.

2.2. Multiobjective Optimization. Network resource optimization problems can be abstracted as multiobjective optimization problems to solve. The existing multiobjective optimization problems usually have three solving methods. The first one is to take a specific objective as the optimization objective and other objectives as constraints, thereby simplifying the multiobjective optimization problem to a single objective optimization problem [3]. The second method is to assign different weights to each goal according to the importance of each goal and use the weight method to get the aggregate objective function through weighted summation of each goal, thereby simplifying the multiobjective optimization problem to a single-objective optimization problem [4]. The third method is multiobjective collaborative optimization. The optimal solution set composed of many Pareto optimal solutions is first jointly optimized according to multiple indicators and then compared and selected according to the optimization direction [10]. Because the optimization requirements for various indicators in multimodal networks are different, this paper adopts a multiobjective collaborative optimization method to optimize network resource allocation.

The evolutionary algorithm of multiobjective collaborative optimization mainly includes multiobjective genetic algorithm, artificial immune algorithm, multiobjective PSO constraint algorithm, and ant colony algorithm [10]. The operation of artificial immune algorithm lacks stability [11], and the research of multiobjective PSO constraint algorithm is still in its infancy [12]. Multiobjective ant colony algorithm will appear premature stagnation, and the control parameters are difficult to determine [13], so the multiobjective genetic algorithm with good robustness and superiority is adopted by this paper [14].

Multiobjective genetic algorithms are widely used in various fields. Reference [15] uses genetic algorithm to solve the MOTSP problem and generates an approximate optimal solution. In Reference [16], from the viewpoint of the minimum actual power loss of the system, genetic algorithms are used to evaluate the impact of the optimal configuration of different types of dg DLMs in the distribution network, and the similarities and differences between different distributed power sources are studied. Reference [17] proposed a multiobjective optimization method that combines artificial neural network and genetic algorithm. Firstly, artificial neural network is used to predict the properties of nanofluids, and then, genetic algorithm is used for multiobjective optimization. As a classic multiobjective collaborative optimization genetic algorithm, NSGA-II adds an elite strategy on the basis of NSGA, adopts the concept of congestion, and reduces the complexity of the algorithm. Reference [4] uses a special fitness function for NSGA-II and uses a method to improve solution diversity. Reference [18] proposes an optimized classification model that constructs linear equations based on classification problems, which can better spread the solution and has higher classification accuracy and robustness.

It can be seen from the above work that there are few researches on power multimodal network resource optimization. In addition, the existing multiobjective optimization model is also difficult to meet the needs of power services that have different QoS requirements for various indicators.

3. Power Multimodal Network Model

As shown in Figure 1, the power multimodal network resource optimization architecture is mainly divided into three layers: a trusted monitoring platform for network resources, multimodal network links, and multimodal network resources. Under the precondition of accurate perception and recognition of multiple services through network monitoring technology, the trusted monitoring platform for network resources uses QoS as a comprehensive evaluation index for network services to analyze multiple network indicators such as delay and reliability, so as to implement unified resource scheduling for multimodal network resources through resource joint optimization strategies.

In general, the physical resources of a multimodal network are relatively fixed. Therefore, the resource optimization of power multimodal network mainly adjusts logical resource allocation through multiobjective collaborative optimization to ensure network service quality. There are many addressing methods for multimodal networks, such as spatial addressing based on content identification, addressing based on geographic location, and addressing based on identity identification [1], which can all be abstracted as the path change of each node in the network. Therefore, this problem can be abstracted as a multiobjective optimization problem of specific business under multimodal network extension [19]. The network topology can be represented as graph $G(V,E)$, where $V=\{v_1,v_2,v_3\cdots v_n\}$ is a collection of nodes and $E=\{e_1,e_2,e_3\cdots e_n\}$ is a collection of node links.

In a multimode network with multiple services, different optimization indicators and requirements are required by different service providers and users [20]. Therefore, according to the network index requirements of different services, the following three types of optimization objectives are considered by this paper: resource overhead of integrated delay and cost, link reliability, and resource occupation distribution. Mapped to the above network model, that is, for any service from the source node to the destination node, a link $L(s,d)=\{l_{s,i},l_{i,j}\cdots l_{k,d}\}$ should be found to satisfy QoS, which reduce resource overhead, reach better reliability, improve link resource utilization, balance network load, and improve network throughput.

3.1. Resource Overhead. In the network topology, the composition of the end-to-end total service delay of the service resource chain is very complicated, which is mainly composed of three parts: link delay, node processing delay, and queuing delay. Considering that the processing delay and queuing delay of nodes in the network link are usually below the microsecond level, while the link delay can normally reach the millisecond level, the impact of link delay on service delay is mainly considered by this paper.

$$\mathrm{Delay}(s,d)=\sum_{i=1}^{n}\sum_{j=1}^{n}\mathrm{delay}(i,j)*\sigma(i,j), \tag{1}$$

where $\mathrm{Delay}(s,d)$ is the total delay of the service link, $\mathrm{delay}(i,j)$ is the delay of the link from node i to node j, and $\sigma(i,j)$ indicates whether the link is selected, which is

$$\sigma(i,j)=\begin{cases}1, & l_{i,j}\in L(s,d),\\ 0, & l_{i,j}\notin L(s,d).\end{cases} \tag{2}$$

At the same time, for a service path, the cost of the service path is measured by the product of the proportion of service bandwidth in each link and the cost of each link.

$$\mathrm{Cost}(s,d)=\sum_{i=1}^{n}\sum_{j=1}^{n}\frac{B(s,d)}{\mathrm{bandwidth}(i,j)}*\mathrm{cost}(i,j)*\sigma(i,j), \tag{3}$$

where $\mathrm{Cost}(s,d)$ is the overall cost of the service link, $B(s,d)$ is the bandwidth required for the service, $\mathrm{bandwidth}(i,j)$ is the remaining bandwidth of each link, and $\mathrm{cost}(i,j)$ is the cost overhead from node i to node j.

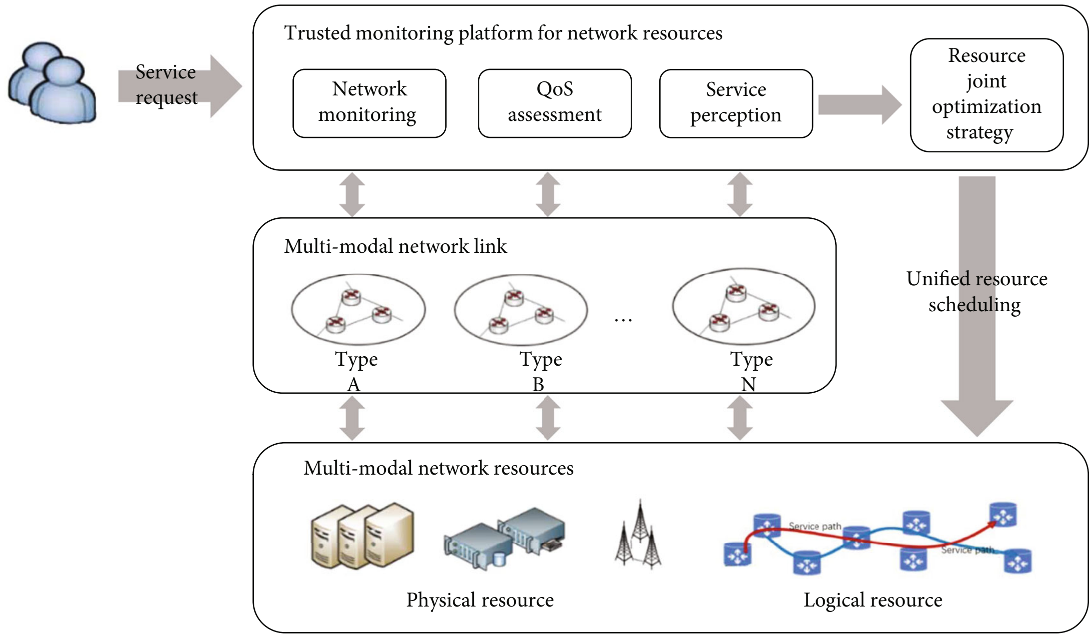

Figure 1: Power multimodal network resource optimization architecture.

The impact of delay time and the cost of reserved resources on the link are considered by this paper comprehensively to measure the network resource cost of the selected path through the resource consumption function as follows.

$$\text{Resource}(s, d) = \text{Delay}(s, d) * \text{Cost}(s, d), \quad (4)$$

where Resource(s, d) is the resource consumption function.

3.2. Link Reliability. According to whether the path matrix is connected and the reliability of each corresponding link, the reliability index of each section is multiplied to calculate the overall reliability index of the link.

$$\text{Reliability}(s, d) = \prod_{l_{i,j} \in L} \text{reliability}(i, j). \quad (5)$$

Among them, Reliability(s, d) is the overall reliability of the service link, and reliability(i, j) is the reliability of the link from node i to node j.

3.3. Resource Occupation Distribution. The proportion of service bandwidth in each link is used to measure resource occupancy in this paper. At the same time, in order to distribute resources evenly on each link, the variance of the proportion of service bandwidth in each link, which is presented by $\delta^2(s, d)$, is used to measure the distribution of occupied resources.

Suppose Utilization$(i, j) = B(s, d)/\text{bandwidth}(i, j)$ is the resource occupation distribution from node i to node j, then

$$\begin{aligned} \text{Utilization}(s, d) &= \frac{\sum_{l_{i,j} \in L} \text{Utilization}(i, j)}{\sum_{l_{i,j} \in L} \sigma(i, j)}, \\ \delta^2(s, d) &= \sum_{l_{i,j} \in L} (\text{Utilization}(i, j) - \text{Utilization}(s, d))^2, \end{aligned} \quad (6)$$

where $B(s, d)$ is the bandwidth required by the current service from the start node s to the destination node d, bandwidth(i, j) is the bandwidth from node i to node j, so Utilization(i, j) represents the bandwidth utilization from node i to node j, and $\delta^2(s, d)$ represents the resource utilization variance from node s to node d.

3.4. Optimization Goals. The goal of multiobjective network resource optimal allocation is to find the optimal solution set as much as possible on the premise of ensuring business QoS indicators according to corresponding business requirements. Therefore, meeting the following conditions should be needed by the selected path:

$$\begin{cases} \text{Min } (\text{Resource}(s, d)), \\ \text{Max } (\text{Reliability}(s, d)), \\ \text{Min } \left(\delta^2(s, d)\right). \end{cases} \quad (7)$$

It can be seen from the above formula that the multimodal network resource optimization results usually hope to obtain the minimum resource consumption, maximum reliability, minimum resource occupation distribution, which is a multiobjective optimization problem with a set of optimal solutions composed of many Pareto optimal solutions, so users can choose the corresponding link according to their business needs.

4. An Optimal Allocation Method of Power Multimodal Network Resources Based on NSGA-II

The general operation process of genetic algorithm is mainly composed of several steps such as coding, initial population generation, fitness function determination, selection method, crossover, and mutation processing.

Aiming at the power multimodal network scenario, a power multimodal network resource optimization allocation method, which designs specific schemes for each step based on the NSGA-II genetic algorithm, is realized by this paper to meet the power business needs.

4.1. Population Initialization

4.1.1. Pretreatment. Before the population is initialized, the input data can be preprocessed to quickly filter out the data links that do not meet the bandwidth requirements, so as to reduce the operation scale of the algorithm. This preprocessing step traverses the network topology and takes the bandwidth required by the business as the standard. All data links smaller than this bandwidth are regarded as nonconnected links. The path is removed from the network topology diagram, so the network links all meet the bandwidth requirements in the final network and the bandwidth constraints will no longer be considered in subsequent studies.

4.1.2. Population Coding. There are usually two ways to initialize population: binary encoding and floating-point encoding. The binary code uses a two-dimensional matrix to represent the data link and uses 1, 0 to indicate whether the link is connected. Usually, a compressed matrix storage method is used to reduce the space occupation, but this kind of representation method is more difficult to verify data connectivity and decoding, so this article uses floating-point encoding. Considering that the length of the network transmission path is not fixed, this article uses an indirect encoding method based on priority encoding [21]. The chromosome based on priority coding does not directly represent the selection path of the current individual, but only the priority of the current node being selected, and the true path corresponding to the chromosome needs to be obtained through a decoding operation.

4.2. Congestion Function. In the genetic evolution algorithm, the fitness function is used to determine the degree of individual adaptation to the "environment," so as to screen outstanding individuals to produce a new generation of populations. The fitness value in the evolutionary algorithm is the function value corresponding to the optimization goal, and the inferior individuals are eliminated by calculating the fitness value.

This algorithm, which draws on the idea of elite selection in the NSGA-II algorithm, firstly calculates the nondominated stratum where each individual in the population is located to achieve population reduction operations and then compares the degree of crowding. Individuals with small nondominated tiers and high crowdedness enter the next iteration to generate new individuals. The calculation formula for congestion $F_i(s, d)$ is

$$F_i(s, d) = \sum_{j=1}^{m} \left(\alpha_j \left| f_j^{i+1} - f_j^{i-1} \right| \right). \tag{8}$$

In the above formula, f_j^{i+1} represents the jth objective function value of the $i + 1$th individual and α_j indicates the weight of the jth objective function value.

Because different service providers and users have different optimization indicators and requirements in network resource optimization, so different weights are assigned to each indicator to meet business needs according to different businesses, and they need to meet $\sum_{j=1}^{m} \alpha_j = 1$.

4.3. Population Selection. In this paper, the best retention selection method is used to select the population. First, the entire population is selected by the roulette method to select the genetic algorithm. The selection probability of the ith individual is $P_i = F_i / \sum_{k=1}^{n} F_k$ (where n is the population size), and then, the structure of the most adaptable individual is completely copied to the next-generation population to complete the selection of the entire population in the current population.

4.4. Population Crossover and Mutation

4.4.1. Population Crossing. Since the general crossover mutation may cause the data link to be blocked and have a negative optimization impact, this paper uses the sequential crossover method to carry out the population crossover operation as follows [14].

(1) Randomly select the start and end positions of several genes in a pair of parental chromosomes (the positions of the two chromosomes are the same)

(2) Generate a progeny based on the selected genes, and ensure the position of the selected gene in the progeny same as the parent

(3) Finally, find out the position of the gene selected in the first step in another parent, and then, put the rest of the genes in order in the offspring generated in the previous step so that a new offspring is produced

It should be noted that this crossover operation will also generate two offspring. The generation process of the other offspring is exactly the same. The genotype position selected in the first step is the same, and only the two parent chromosomes need to be exchanged.

4.4.2. Population Variation. The population generated after fitness calculation, selection, and crossover may converge to the local optimal solution instead of the global optimal solution. Therefore, mutation operation is needed to promote the population to jump out of the local optimal situation. In this paper, the chromosome segment reverse

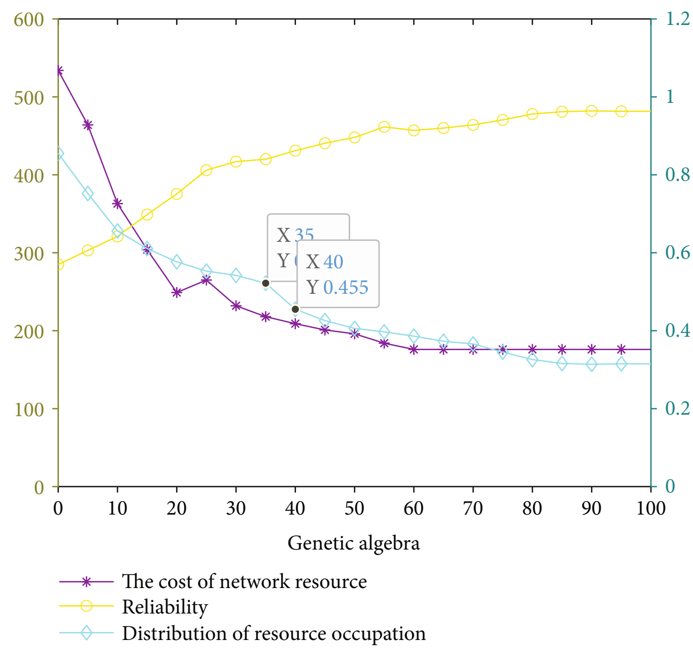

Figure 2: The change trend of various indicators in the genetic process.

transformation is performed on the new individuals generated by the crossover with a certain probability, and the result of the mutation will check whether the link is connected. If the link is connected, join the population; if not, perform a population selection operation to replace the path.

4.5. Restrictions. Assuming that each node in the network has enough buffer space to store packet data, the algorithm should meet the following conditions during each genetic evolution in order to ensure that the network is not congested and the selected path starts from the source node s and ends at the destination node d:

(1) The selected network link should avoid network congestion as much as possible, namely, Utilization $(s, d) < 1$

(2) At least one optional link $L(s, d)$ exists bandwidth$_l$ $< B, l \in L(s, d)$

4.6. Algorithm Flow. According to the above model construction and multiobjective optimization algorithm selection, the algorithm process of the NSGA-II-based multiobjective network resource optimization allocation method is as follows:

(1) Initialize the random network and scale-free network populations, and set the population size and the maximum number of evolutions

(2) Preprocess the initial network topology map to filter out network links that do not meet the bandwidth requirements

(3) Starting from the second generation, merge the parent and offspring to form a large population, perform quick nondominated sorting on it, and then, calculate the crowding degree for each nondominated level individual, and finally according to the nondominated relationship and crowding degree to select suitable individuals to form a new parent population

(4) Decode the population individuals to get the true network path

(5) Perform selection, crossover, and mutation operations to produce new offspring populations

(6) If the genetic algebra exceeds the set value, go to Step 7; otherwise, go to Step 3

(7) Output the optimal solution, and choose according to the specific network business requirements

5. Simulation Analysis

In this section, we evaluate the optimal allocation method of power multimodal network resources based on NSGA-II and compare it with other algorithms.

5.1. Results of Resource Allocation. In the power multimodal network, the network nodes and the links are very complex and difficult to abstract. Therefore, this paper uses 20 network nodes as examples to test, and the link bandwidth, delay, reliability, and other data are randomly generated within a reasonable range. The specific parameters in the experiment are set as follows: the number of network nodes is 20, the initial population size is 200, the genetic algebra is 100, the crossover probability XOVR $= 0.8$, the mutation probability $p_m = 0.1$, the crossover probability $p_c = 0.9$, the source node is 1, and the purpose node is 20. Using the above resource optimization method to carry out simulation

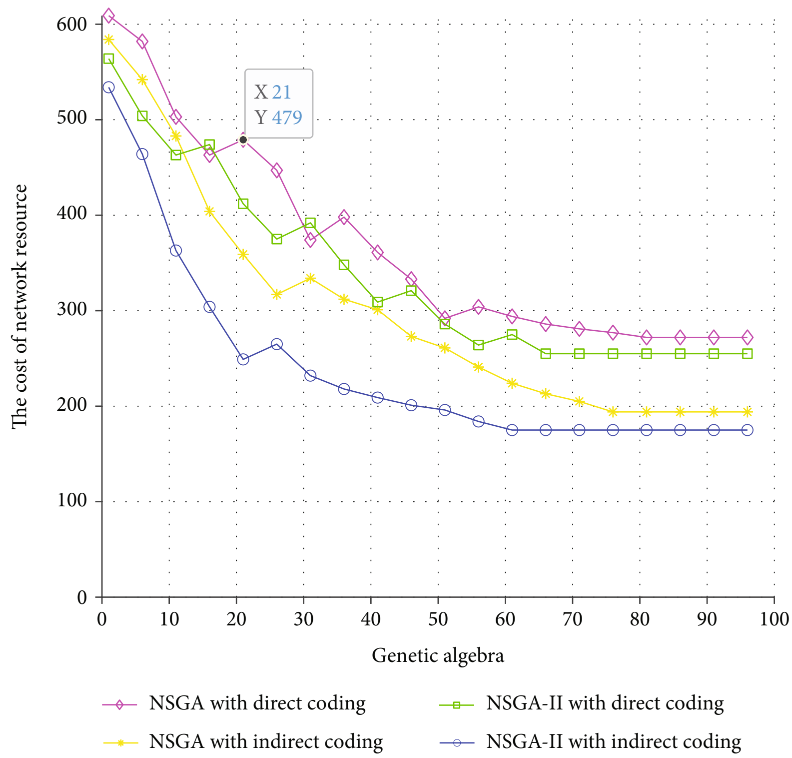

Figure 3: Changes in the resource expenditure of each experimental group in the genetic process.

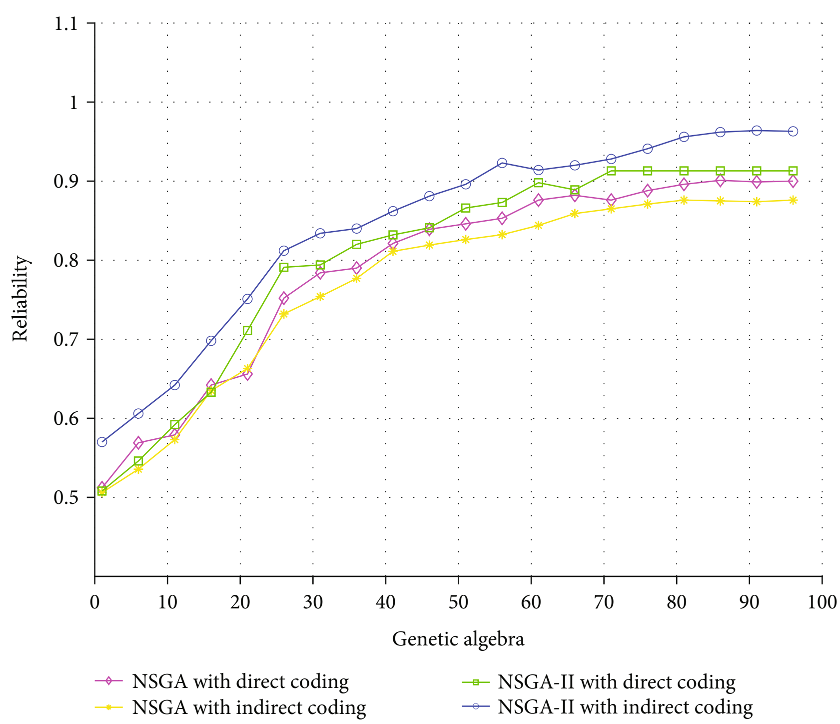

Figure 4: Changes in the link reliability of each experimental group in the genetic process.

experiments, the multiobjective network resource optimization result is shown in Figure 2.

Because the algorithm preprocesses remove the network links that do not meet the bandwidth requirements and simplify the calculation scale of the genetic algorithm before running, the entire process can be completed faster than usual. From Figure 2, it can be seen that the resource cost is continuously reduced to a stable state during the genetic process, indicating that the genetic algorithm can stably optimize the population, obtain the optimal value, and

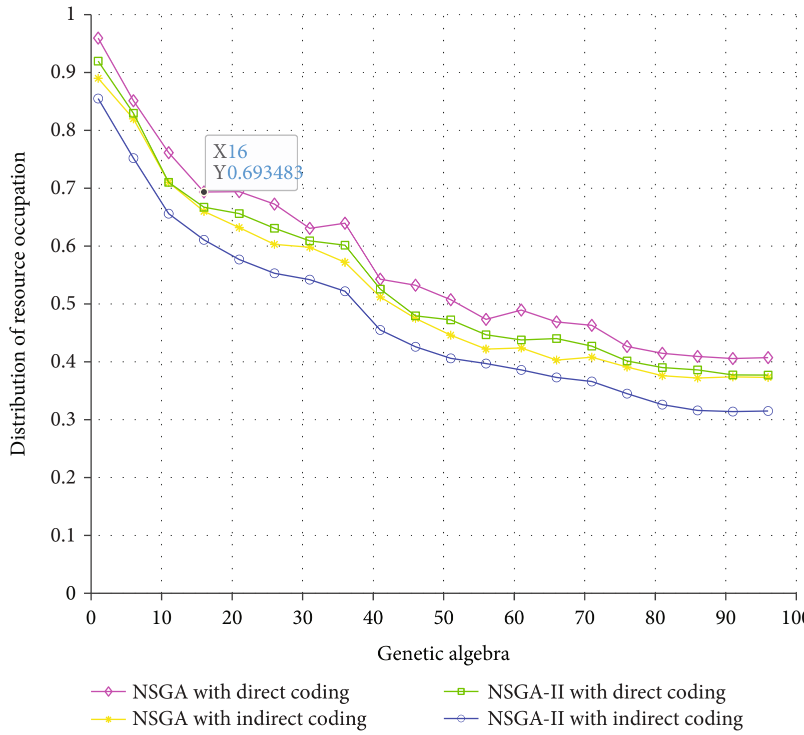

Figure 5: Variation trend of the distribution of resources occupied by each experimental group in the genetic process.

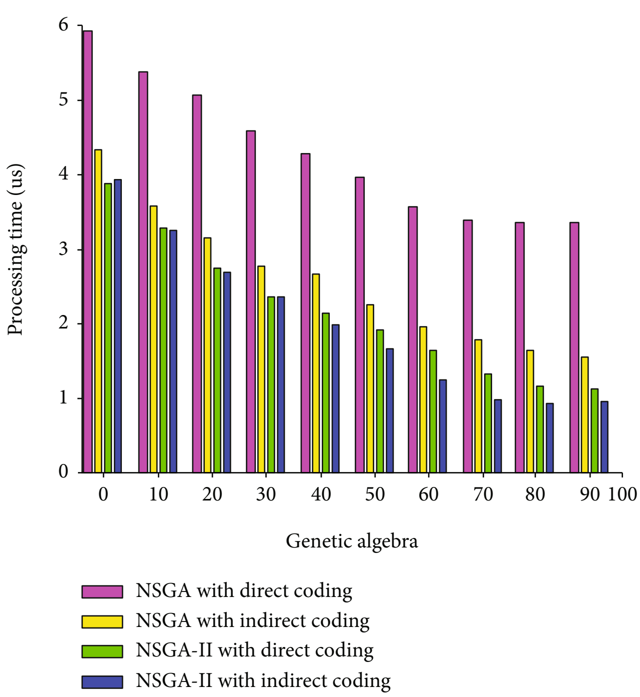

Figure 6: Convergence comparison between this genetic algorithm and other genetic algorithms.

quickly jump out of the local optimal solution to reach the state of the global optimal solution during the entire process.

Because the mutation probability in this experiment is $p_m \in (0, 1)$, $p_c \in (0, 1)$, and the genetic algorithm that retains the current optimal solution before selection can converge to the global optimal solution, it can be seen that the algorithm can converge to the global optimal solution [22].

5.2. Algorithm Performance. The performance of the algorithm is analyzed in two aspects. The first part is the change trend of various optimization indicators of the algorithm and other algorithms in the genetic process, and the second part is the convergence comparison between the algorithm and other algorithms.

In order to verify the effectiveness and convergence of the algorithm, we selected the classic multiobjective genetic algorithm NSGA and NSGA-II genetic algorithm to compare with the method in this paper. In order to verify the effectiveness of the method, we selected four experimental groups, arranged as follows. In the case of the same model, experimental group 1 adopts NSGA with direct encoding, experimental group 2 adopts NSGA with indirect encoding, experimental group 3 adopts NSGA-II with direct encoding, and experimental group 4 adopts the method of this article.

In Figure 3, the optimization results of the above four experimental groups for resource overhead are compared. It can be seen that disconnected paths are often generated in the cross-mutation process of the population in experimental group 1 and experimental group 3 with direct coding, which leads to negative optimization and unstable optimization results. However, experimental group 2 and experimental group 4 occasionally have negative optimization, but they will quickly stabilize and produce final results.

Figure 4 shows the change trend of the link reliability of each experimental group with the genetic algebra. It can be seen that the reliability of all experimental groups is gradually increasing. However, experimental group 1 and experimental group 3 showed a fluctuating upward trend, and the optimization results were not stable enough. Both experimental group 2 and experimental group 4 grow steadily, but experimental group 2 tends to fall into the state of local optimal solution due to the limitation of the algorithm, so on the whole, experimental group 4 can reach the optimal solution quickly and steadily.

In Figure 5, the change trend of the resource occupation distribution of each experimental group is compared. It can be seen that all the experimental groups showed a downward trend as a whole. But with the increase of genetic algebra, the optimization value slows down. This is because with the increase of the genetic algebra, the population individuals gradually tend to the optimal solution, and each time the genetic change is not large, the overall optimization slowdown is slowed down. It can be seen from the figure that the NSGA-II-based power multimodal network resource optimization allocation method proposed in this paper reduces the distribution of resource occupation to the greatest extent and has a better optimization effect than other experimental groups.

Figure 6 is a comparison of the convergence between different algorithms. Although the algorithm has a longer running time due to preprocessing at the beginning, the network chain that does not meet the bandwidth requirements is removed in the process, which simplifies the calculation scale of the subsequent genetic algorithm. So the entire process can be completed faster than others, which further shows that the algorithm has high convergence and good reliability.

6. Conclusion

Unstable power business services are caused by the complex and changeable power multimodal network, which is difficult to meet the QoS requirements of different businesses. In order to ensure the normal operation of power business and improve resource utilization, an optimal allocation method of power multimodal network resources based on NSGA-II was proposed by this paper. Firstly, the power multimodal network-resource model is established, and the problems existing in the resource optimization process are analyzed. Secondly, preprocessing technology and indirect coding technology are applied to NSGA-II, which solves the coding problem and convergence problem of the application of genetic algorithm to the optimization of network resource allocation. Finally, the simulation results show that, compared with the control algorithm, this method has further optimized the various indicators of the resource allocation of the power multimodal network, and the performance has been improved by more than 6%.

However, the addition of preprocessing makes the algorithm often take a lot of time in the early stage of operation. In addition, because the model pays more attention to the fast response in time, it takes up a lot of memory space during the operation. This is the direction that needs attention and optimization in future work. We will consider improving the preprocessing algorithm to reduce the initial running time of the algorithm, and by optimizing the genetic method of NSGA-II, we will improve the power multimodal network resource optimization allocation method to reduce the memory space occupation during the algorithm operation.

Data Availability

The result data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] H. U. Yuxiang, Y. I. Peng, S. U. N. Penghao, and W. U. Jiangxing, "Research on the full-dimensional defined polymorphic smart network," *Journal on Communications*, vol. 40, no. 8, pp. 1–12, 2019.

[2] M. Cremene, M. Suciu, D. Pallez, and D. Dumitrescu, "Comparative analysis of multi-objective evolutionary algorithms for QoS-aware web service composition," *Applied Soft Computing*, vol. 39, pp. 124–139, 2016.

[3] K. Deb, *Multi-Objective Optimization Using Evolutionary Algorithms*, John Wiley & Sons, 2001.

[4] A. Konak, D. W. Coit, and A. E. Smith, "Multi-objective optimization using genetic algorithms: a tutorial," *Reliability Engineering & System Safety*, vol. 91, no. 9, pp. 992–1007, 2006.

[5] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 2, pp. 182–197, 2002.

[6] C. U. I. Limin, S. U. N. Jingyue, L. I. Shanjun, and S. O. N. G. Guanglei, "An algorithm for business resource uniform distribution in power communication network based on entropy," *Power System Technology*, vol. 9, pp. 3066–3073, 2017.

[7] O. S. Yeremenko, O. V. Lemeshko, O. S. Nevzorova, and A. M. Hailan, "Method of hierarchical QoS routing based on network resource reservation," in *2017 IEEE First Ukraine Conference on Electrical and Computer Engineering (UKRCON)*, pp. 971–976, IEEE, Kyiv, UKraine, 2017.

[8] T. Chen, Q. Ling, and G. B. Giannakis, "An online convex optimization approach to proactive network resource allocation," *IEEE Transactions on Signal Processing*, vol. 65, no. 24, pp. 6350–6364, 2017.

[9] Y. T. Leong, J. Y. Lee, R. R. Tan, J. J. Foo, and I. M. L. Chew, "Multi-objective optimization for resource network synthesis in eco-industrial parks using an integrated analytic hierarchy process," *Journal of Cleaner Production*, vol. 143, pp. 1268–1283, 2017.

[10] N. Gunantara, "A review of multi-objective optimization: methods and its applications," *Cogent Engineering*, vol. 5, no. 1, p. 1502242, 2018.

[11] D. Dasgupta, *Artificial immune systems and their applications*, Springer Science & Business Media, 2012.

[12] H. Garg, "A hybrid PSO-GA algorithm for constrained optimization problems," *Applied Mathematics and Computation*, vol. 274, pp. 292–305, 2016.

[13] Y. Gao, H. Guan, Z. Qi, Y. Hou, and L. Liu, "A multi-objective ant colony system algorithm for virtual machine placement in cloud computing," *Journal of Computer and System Sciences*, vol. 79, no. 8, pp. 1230–1242, 2013.

[14] T. Murata and H. Ishibuchi, "MOGA: multi-objective genetic algorithms," *IEEE international conference on evolutionary computation*, vol. 1, pp. 289–294, 1995.

[15] T. George and T. Amudha, "Genetic algorithm based multi-objective optimization framework to solve traveling salesman problem," in *Advances in Computing and Intelligent Systems*, pp. 141–151, Springer, Singapore, 2020.

[16] B. Singh, V. Mukherjee, and P. Tiwari, "GA-based multi-objective optimization for distributed generations planning with DLMs in distribution power systems," *Journal of Electrical Systems and Information Technology*, vol. 4, no. 1, pp. 62–94, 2017.

[17] S. A. Bagherzadeh, M. T. Sulgani, V. Nikkhah, M. Bahrami, A. Karimipour, and Y. Jiang, "Minimize pressure drop and maximize heat transfer coefficient by the new proposed multi-objective optimization/statistical model composed of "ANN + genetic algorithm" based on empirical data of CuO/-paraffin nanofluid in a pipe," *Physica A: Statistical Mechanics and its Applications*, vol. 527, p. 121056, 2019.

[18] B. Zhao, Y. Xue, B. Xu, T. Ma, and J. Liu, "Multi-objective classification based on NSGA-II," *International Journal of Computing Science and Mathematics*, vol. 9, no. 6, pp. 539–546, 2018.

[19] B. Tan, H. Ma, and Y. Mei, "A NSGA-II-based approach for service resource allocation in cloud," in *2017 IEEE Congress on Evolutionary Computation (CEC)*, pp. 2574–2581, IEEE, Donostia, Spain, 2017.

[20] A. S. MSofia and K. P. Ganesh, "Multi-objective task scheduling to minimize energy consumption and makespan of cloud computing using NSGA-II," *Journal of Network and Systems Management*, vol. 26, no. 2, pp. 463–485, 2018.

[21] L. Lin and M. Gen, "Priority-based genetic algorithm for shortest path routing problem in OSPF," in *Intelligent and Evolutionary Systems*, pp. 91–103, Springer, Berlin, Heidelberg, 2009.

[22] R. H. Hwang, W. Y. Do, and S. C. Yang, "Multicast routing based on genetic algorithms," *Journal of Information Science and Engineering*, vol. 16, no. 6, pp. 885–901, 2000.