scientific reports

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# Network carrier allocation optimization based on immune algorithm under massive concurrent access

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**In small multi-functional base stations such as 230 MHz power wireless private network LTE, when there is concurrent transient access of a large number of terminals, issues such as packet blocking and loss frequently occur, severely degrading overall system performance. To this end, the total delay during data transmission and queuing in the massive concurrent access of the power wireless private network is modeled, and a carrier allocation optimization method based on the optimized heuristic algorithm - immune algorithm is proposed. First, for the multi-objective problem with high real-time data requirements and packet loss rate requirements in the problem, an operational research model of data delay mechanism is constructed with the total data transmission delay as the objective function; An optimal resource allocation method based on immune algorithm is proposed to optimize the solution process; The minimum existence and convergence of the data delay model were analyzed and proved. The experimental results show that in the case of massive concurrent access, the proposed method enables the base station to maintain more stable performance under carrier limitations and massive concurrent access.**

**Keywords** Power wireless private network, Immune algorithm, Carrier allocation, Massive concurrent access, Minimum delay

**Abbreviations**

| | |
|---|---|
| mMTC | Massive machine type communications |
| LTE | Long-term evolution |
| D2D | Device to device |
| AIA | Artificial immune algorithm |
| POS | Priority queue scheduling |
| DBA | Dynamic bandwidth allocation |
| ES | Elitism strategy |
| IC | Incremental calculation |
| AMR | Adaptive mutation rate |

With the development of vertical industries such as the Industrial Internet of Power Systems, wireless communication scenarios to large user groups will become one of the main application scenarios for future communication networks[1]. The number of machine-like device terminals in the smart grid is surging, and network resources are limited. Existing technologies cannot effectively meet the requirements of access success rate, latency and system complexity in the smart grid[2]. Meanwhile, promoting the transformation of existing wireless communication technologies into intelligent wireless communication with massive access has become an important direction for building 6G mobile communication network architecture solutions and new access technologies for dealing with massive data transmission[3]. In the case of a rapid increase in the number of service access terminals, such as when there is a large-scale fault in the power system, such as grid interruption, equipment damage, or damage to the power system caused by natural disasters (such as earthquakes, floods, etc.), and a large number of repair equipment needs to be quickly put into repair work, the terminals may be connected to the power wireless private network simultaneously[4]; Furthermore, during major dispatching or operational events in the power system, during certain special periods such as peak electricity consumption, holidays or major events, a large number of terminals need to be concurrently connected to the power wireless

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private network for monitoring and regulation; As the proportion of new energy (such as wind power, solar power, etc.) in the power system keeps increasing, the volatility of new energy generation may also lead to massive access of terminals[5,6]. Under massive concurrent access, whether through random access or competing access with only 64 selectable leading sequences, it is extremely prone to problems such as blocking, delay, and packet loss. With the increase in the number of terminals, the average access delay increments. For a case where the maximum number of retransmissions of the leading sequence is 8 and the number of terminals is 3000, the access delay reaches 400 milliseconds. And due to the carrier limitation of LTE230M, when a large number of terminals send data simultaneously, a carrier bottleneck may be encountered, resulting in a significant decrease in data transmission rate, which has a significant impact on the transmission of data with high real-time requirements under the private network[7].

Immune algorithms incorporate the characteristics of genetic algorithms and have diversity maintenance and learning mechanisms, making them more effective than genetic algorithms in multi-peak function optimization. It can effectively search for the global optimal solution, is less dependent on the problem and the initial solution, and has strong adaptability and robustness. Immune algorithms can find solutions to problems with relatively few iterations and perform well in scenarios that require fast computation. The parallel optimization capabilities of immune algorithms enable them to significantly increase computing speed when dealing with large-scale problems. The main work of this paper is as follows:

(1) In response to the problem of severe packet loss and congestion caused by excessive data packets and data volume in the cellular network of the power wireless private network when facing sudden massive concurrent access, which leads to a sharp decline in the efficiency of the communication system, under the constraint of 230 MHz, considering the diversity of data packet types and discrete spectrum allocation strategy, with the goal of minimizing the overall delay of data packet transmission. A comprehensive data packet delay model and corresponding constraints for private cellular networks are established;
(2) Considering the main problems that the immune algorithm is prone to fall into local optimum and the computing speed cannot meet the real-time requirements when solving the carrier allocation constraint model of massive concurrent access data packets, the P-D-E resource optimization allocation strategy, the IC population refresh optimization strategy and the AMR mutation optimization strategy are proposed, and the calculation process is given.
(3) Simulation analysis of the established carrier allocation model based on immune algorithm optimization. Compare and analyze with other carrier allocation optimization models, taking into account the data volume and the proportion of data packet types when there is massive access. Verify that the proposed method ensures better stability of data packet transmission under limited carrier resources, and verify the rationality of the scheme that base station communication is the most stable under massive access. See Fig. 1.

## Related work

### Research on massive concurrent data and carrier resource allocation

The random access mechanism of the LTE system has become the main bottleneck for concurrent massive data transmission in power wireless private networks. The access delay and blockage caused by the proliferation of terminals seriously affect the real-time performance[1,8]. In terms of access strategy optimization, literature[8] reduces blocking probability by increasing the number of retransmission of preemble sequence, but it will increase delay and collision risk. Literature[9] proposed an uplink resource allocation algorithm based on sleeping multi-armed bandit. Literature[10] innovates dual sequence diversity competitive access, taking into account both license-free efficiency and massive user adaptation ability. In the research of access mode, literature[11] proposed centralized wired, distributed wireless and hybrid access schemes for multi-service scenarios. Literature[12] designed the information operation and maintenance optimization system of Internet of things based on cloud computing. Literature[13] proposed a differentiated large-scale access scheme combining congestion control and multi-user detection. Literature[14] introduces weighted kNN method to realize high-dimensional data anomaly detection. For 6G mass access, GF-NOMA resource allocation scheme was proposed in literature[15] to adapt to dynamic service requirements.

In view of the shortage of spectrum resources, research on communication resource allocation focuses on multi-dimensional optimization: (1) network architecture optimization: literature[16] proposes a base station cluster cooperative management strategy; Literature[17] constructed a resource allocation optimization model based on quantum genetic algorithm. (2) UAV relaying and energy efficiency balance: Literature[18,19] respectively studied the fairness optimization and rate maximization problem under energy consumption constraint in UAV relaying scenario. (3) Communication and sensing integration: Literature[20] proposed a resource allocation method driven by spectrum reuse criteria; (4) Fairness and mode selection: Literature[21] optimizes RSMA spatial resource allocation with the objective of maximizing the minimum user rate; Literature[22] proposed a joint optimization algorithm of mode selection and channel assignment for cellular single cell.

### Main shortcomings

However, there is a research gap in the targeted optimization of the special requirements of power wireless private networks in the vast number of concurrent transient access studies, and few studies have conducted in-depth analysis of this problem through the method of constrained extremum optimization. Existing resource allocation optimization models cannot achieve good results in the massive concurrent transient access of power wireless private network cellular networks and cannot be well invoked. Therefore, this paper presents a carrier allocation optimization method based on the optimized heuristic algorithm - Immune Algorithm (AIA). With the goal of minimizing data packet transmission delay, a data packet transmission delay model is constructed through discrete carrier aggregation technology. Considering the influence of queuing delay, transmission delay and

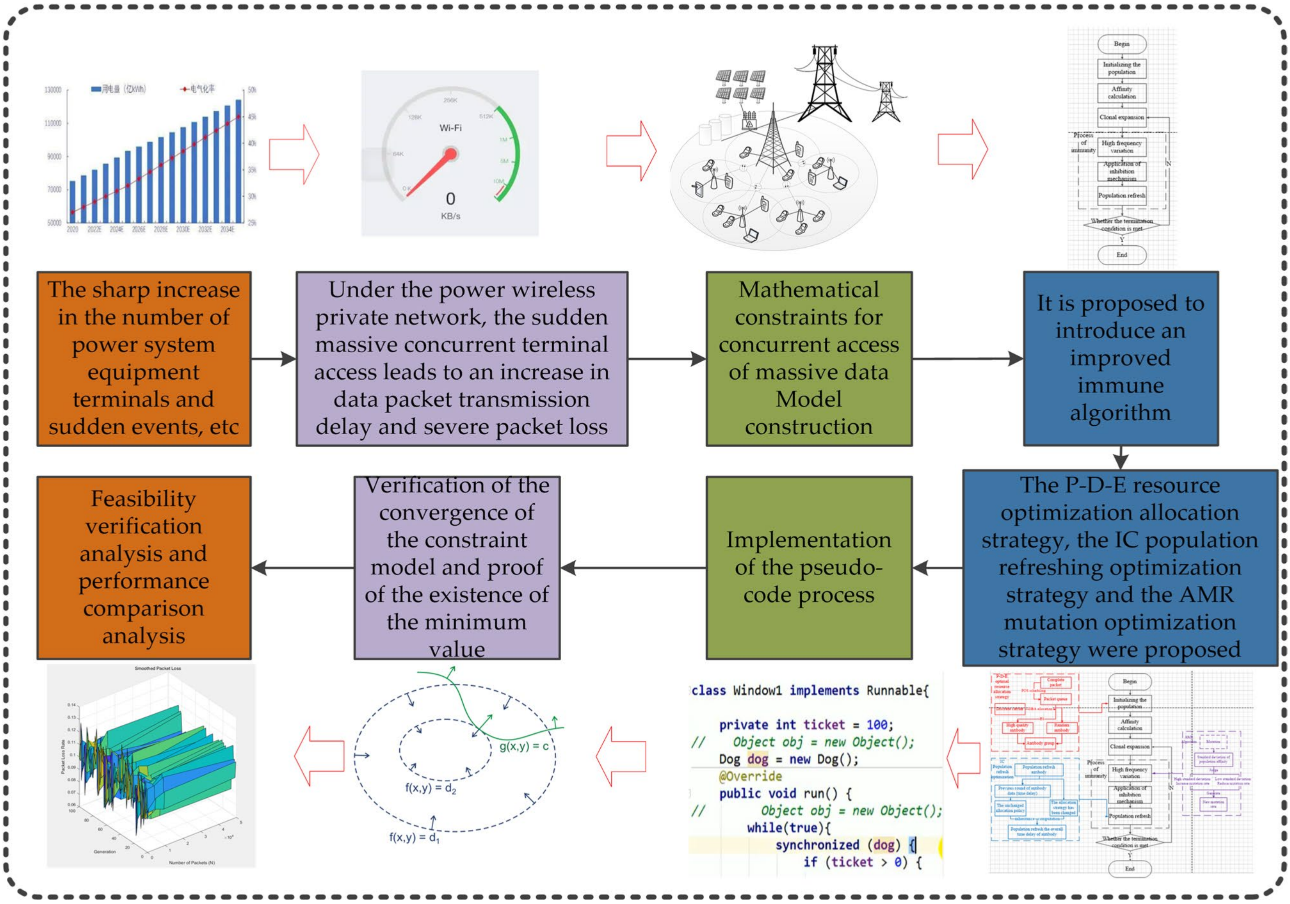



**Fig. 1**. Diagram of the process for optimizing the allocation of private network resource.

carrier allocation strategy, the carrier allocation problem is transformed into a multi-constrained combinatorial optimization problem. The P-D-E resource optimization allocation strategy is proposed to optimize the antibody generation process, and the IC population refresh optimization and AMR mutation optimization methods are proposed to solve the problem that the immune algorithm is prone to fall into local optimum during calculation and the calculation speed cannot meet the real-time requirements. Ultimately, it solves the problem of low communication efficiency caused by packet loss and blocking when massive concurrent access occurs in the cellular network of power wireless private networks.

## Concurrent access delay modeling

### Delay model

Access terminal service packet forwarding delay consists of three parts: cache delay, transmission delay, and queuing delay.

Cache delay: Cache delay is relatively small compared to transport delay and queue delay, and mainly depends on the hardware conditions of the cache. To simplify the model, this part of the delay is uniformly set as $\tau_c$.

Transmission delay: Each data packet m is cached in the cache and then transmitted in parallel on the channel after leaving the cache. Therefore, this part of the delay mainly includes the transmission delay. The size of the packet m is defined as λ, and the transmission rate is $D_m$, often determined by combining the Shannon formula, etc. In the power wireless private network, considering the different frequency bands, the rate is simplified into three categories: high real-time, large capacity data: requires low latency and large volume of data transmission; High real-time, small capacity data: requires low latency, but the data volume is small; Low real-time, large volume data: The latency requirements are not as strict as the former two, but the data volume is large.

Transmission delay can be expressed as:

$$\tau_{\rm m} = \frac{D_m}{\lambda_m} \tag{1}$$

Queuing delay: In a certain frequency band, power communication service data packets enter the base station to create a new sorting relationship. For ease of expression, the concept of virtual transport device VTP is introduced to distinguish it, and the VTP set is defined as $N = \{1,2,\ldots\ldots n,\ldots. N\}$ and satisfies N = M. It is called virtual because the position is not formed before transmission, but the data packets on the channel network are split into separate entities by the guard band, as if each data packet occupies a transmission position separately.

Establish an index relation matrix $[\Phi_{m,n}]$ to represent the position correspondence of packets before and after scheduling, the value of each element in the matrix is either 0 or 1. when a certain element in the matrix $\Phi_{m,n}$= 1, the data packet at the NTH VTP on the channel is the data packet m before scheduling, otherwise $\Phi_{m,n}$ = 0. For example: If packet 1 occupies VTP2 after scheduling, then $\Phi_{1,2}$(denotes the mutual affinity between antibody 1 and antibody 2, reflecting similarity between their scheduling patterns.) = 0, the traffic scheduling model we are studying has no packet loss and no aliasing occurs, so satisfy:

$$\sum_{\mathrm{n}\,=\,1}^{N} \Phi_{\mathrm{mn}} = 1 \qquad \sum_{\mathrm{m}\,=\,1}^{N} \Phi_{\mathrm{mn}} = 1 \tag{2}$$

For the power communication service data packet m at the NTH VTP, its queuing delay can be split into the cache delay of the first n-1 packets and the transmission delay of the first n-1 packets. It is ultimately expressed as:

$$\tau_{m,n}^{Q} = (n-1)\,\tau^{P} + \sum_{v=1}^{M}\sum_{i=1}^{n-1} \Phi_{v,1}\tau_{v}^{T} \tag{3}$$

## Resource allocation model

The total delay of the access terminal data packet is:

$$\tau_{m,n} = \tau^{C} + \tau_{m,n}^{Q} + \tau_{m}^{T} \tag{4}$$

The utility function (objective function) of total forwarding delay and priority scheduling under all packets is:

$$\min D = \sum_{m=1}^{N} a_m/\tau_{m,n} \tag{5}$$

$a_m$ represents the scheduling and sorting of different power business data packets. The larger the $a_m$, the higher the sequence, that is, the higher the priority. The constraints are:

$$\begin{aligned} s.t.\quad & C_1 : \sum_{m=1}^{N} b_m \leq C_{link} \\ & C_2 : \sum_{m=1}^{N} r_m \leq C_{node} \\ & C_3 : \sum_{n=1}^{N} \Phi_{m,n} = 1 \\ & C_4 : \sum_{m=1}^{N} \Phi_{m,n} = 1 \\ & C_5 : \sum_{i=1}^{4} B_i \leq 1\,\mathrm{MHz} \\ & C_6 : B_i \in \{25\,KHz, 50\,KHz, 100\,KHz,\ 200KHz\} \end{aligned} \tag{6}$$

Where $C_1$ is the maximum throughput limit of the link, bi is the carrier requirement for the MTH packet, and $C_{link}$ is the maximum throughput of the link; $C_2$ is the maximum processing capacity limit of the node, $r_i$ is the processing rate requirement of the MTH data packet, and $C_{node}$ is the maximum processing capacity of the node; $C_3$ indicates that each packet corresponds to a VTP, that is, the system has no packet loss; $C_4$ indicates that each VTP can only be occupied by one packet, that aliasing will not occur; $C_5$ indicates that the total bandwidth cannot exceed 1 MHz; $C_6$ indicates that the carrier assigned to each data type can only be a combination of these standard values.

# Algorithmic process

## Dynamic carrier aggregation method based on Immune algorithm

(1) Initialization: Randomly generate multiple initial antibodies based on the system state, that is, a series of possible packet transmission paths and scheduling strategies, which constitute the antibody population. Each antibody represents a possible scheduling scheme.

The channel carrier allocation is represented using discrete coding, as follows:

$$x = [B_1, B_2, ..., B_N] \tag{7}$$

Among them, $B_N$ is the carrier allocation, with values of {25,50,100,200} KHz. Set the population size to $N_p$, generate random individuals, and satisfy the constraints of $C_4$, $C_5$, $C_6$, and regenerate if the constraints are not met.

(2) Affinity evaluation: Evaluate the affinity of each individual in the population (i.e., each transport path and scheduling policy) and calculate the affinity value. The affinity function is defined as:

$$F(x) = \frac{1}{D} \tag{8}$$

Introduce a penalty mechanism and add a penalty item:

$$G(x)\text{=-}\sum_{m=1}^{N} a_m/\tau_{m,n}+\lambda_1 P_{\text{link}}+\lambda_2 P_{\text{node}}+\lambda_3 P_{SLFC}$$

Where $P_{link}$ is the penalty value for violating the link throughput limit, $P_{node}$ is the penalty value for violating the node throughput limit, $P_{SLFC}$ is the penalty value for violating the single forwarding delay constraint, and $\lambda_1$, $\lambda_2$, $\lambda_3$ are the penalty factor weights respectively.

(3) Selection: Select the individual to proceed to the next step by roulette to avoid premature convergence to a local optimal solution while retaining high-quality antibodies, namely paths and scheduling strategies with smaller overall delay. The probability of an individual being selected is:

$$P_{\text{m}}=\frac{F_{\text{m}}}{\sum_{j=1}^{N_p} F_m} \tag{10}$$

Where $P_{\text{m}}$ is the probability of being selected and $F_{\text{m}}$ is individual affinity Value, $\sum_{j=1}^{N_p} F_m$ is sum of individual affinity, for normalizing.

(4) Cloning and variation: Select antibodies with higher affinity based on the affinity value for cloning, and the number of clones is proportional to the affinity value. The individual clone quantity function is:

$$C_i=\alpha\cdot(1\text{-}\frac{F_{\text{m}}}{F_{\text{max}}}) \tag{11}$$

Mutate the cloned individuals and randomly adjust the carrier allocation to increase population diversity. The mutation probability for each individual in the population is set to Pm, and the mutation method is to modify the broadband value, selected from {25,50,100,200} KHz, and ensure that the constraint limit of $C_5$ is satisfied.

(5) Clone inhibition: Test the newly generated individuals and update the memory based on the newly generated antibody affinity value to retain the current optimal antibody. If the overall delay is small, replace the low-quality individuals. Calculate the similarity between individuals at the same time to avoid overcrowding of the population. The similarity calculation function is:

$$S(x_m, x_n) = \frac{1}{N}\sum_{k=1}^{N} \delta(B_k^i, B_k^j) \tag{12}$$

Where $\delta$ is the discriminant function, if $B_k^i = B_k^j$, then$\delta = 1$, and vice versa is 0. When similarity exceeds the threshold, individuals with higher affinity are retained and those with lower affinity are removed.

(6) Population refresh: Replace the antibodies with lower affinity in the original population with a randomly generated new antibody memory bank (new transport paths and scheduling strategies), while retaining the

historical optimal solution to prevent the loss of the global optimum and form a new generation of antibody populations.

(7) Iterative optimization: Repeat the above steps until the maximum number of iterations $T_{max}$ (indicates the maximum number of iterations.) is met or the variation of the optimal solution is less than the threshold, and output the optimal solution.

## Model extremum solution optimization strategy based on IA algorithm

### Dynamic carrier resource optimization strategy based on high-impact data

In initialization, to improve convergence speed and avoid getting stuck in local optima, the antibodies are divided into two categories: generating partially high-quality initial antibodies based on problem characteristics and random antibodies. Introducing Priority Queue Scheduling (POS), Dynamic Bandwidth Allocation (DBA), and Elitism Strategy (ES), The P-D-E algorithm is proposed. First, sort the packets by priority and size to ensure that the high-priority and small packets are scheduled first. Then, allocate a larger bandwidth to the high-priority packets to ensure that the delay of the critical packets is minimized. At the same time, use a random allocation strategy for some antibodies to enhance diversity and avoid the algorithm falling into local optima.

### Population refresh strategy based on incremental computation

Introduce Incremental Calculation (IC) in the population refresh section, recalculating the delay only for the part where the scheduling scheme changes, and reusing the results of the previous iteration for the rest. Record the current scheduling solution S and the corresponding bandwidth of the data packet, retain the delay result $T_{prev}$ of the corresponding data packet, and generate the set $M_{changed}$ of all affected data packets.

### Global preservation strategy under the optimal solution

The Adaptive Mutation Rate (AMR) method is proposed to enable stronger mutation operations at the appropriate time, which helps search to jump out of the local optimal solution and reduce the mutation rate as it approaches the global optimal solution, avoiding unnecessary computational waste. At the beginning of the search, the affinity difference is large and the mutation rate is high, ensuring that the algorithm can search the solution space extensively; In the later stage, as the affinity difference decreases, the rate of variation should gradually decrease in order to find the global optimal solution more precisely. Adjust the mechanism by calculating the standard deviation of affinity. And set up an adaptive rate of variation adjustment function, which adaptively adjusts the rate of variation according to the differences in population affinity, ensuring that populations with high diversity maintain high variation and otherwise maintain low variation.

The three optimization strategies based on the immune algorithm mentioned above are combined and named as the fast optimal Value Solving optimization Strategy based on the immune algorithm. Present the calculation process and logic of the three proposed optimization strategies throughout the entire immune algorithm process in the form of a flowchart. As shown in Fig. 2.

### Simulation analysis

A specific scenario is selected for detailed analysis. Considering that multiple distributed energy management systems within the power wireless private network may face sudden situations under special circumstances, simulation data Settings and analyses are conducted for the sudden transmission of massive concurrent data by systems within the private network area after power restoration, as shown in the above Fig. 3.

After the power is restored, the system in the dedicated network area suddenly transmits a huge amount of concurrent data, mainly including a large number of terminal user devices such as photovoltaic power stations and small wind turbines (low real-time big data), accounting for 40%, and real-time operating parameters of distributed energy equipment such as inverter temperature, wind speed, and light intensity (high real-time big data), accounting for 40%. The remote control data (high real-time small data) issued by the power dispatching center to distributed energy equipment for operations such as the start and stop of inverters, the charging and discharging instructions of energy storage systems, and the opening and closing operations of intelligent switches accounts for 20%.

There are three types of power access terminals: distribution type, consumption type and precision load control type. Distribution equipment includes low-voltage distribution cabinets, etc. The acquisition terminals include smart meters, sensors, remote terminal units, etc. Precision control terminals include smart circuit breakers, edge computing devices, etc. In this scenario, capacity planning is based on the number of concurrent users, with the precision control terminal calculated at 100% concurrent rate, the distribution terminal at 100% concurrent rate, and the power consumption terminal at 10% concurrent rate[9]. If there are 94 frequency points in the area, the precision control resource pool has 14 frequency points, the distribution resource pool has 40 frequency points, and the power consumption resource pool has 40 frequency points. The maximum number of distribution points that can be connected is 92; The maximum number of power distributions available for access is 920. In addition, the total capacity of the area cannot exceed the number of online users. As shown in Fig. 1.

### Algorithm convergence analysis

Establish a constraint function for the problem of packet blocking and severe delay in the context of massive concurrent access terminals, consider using the immune algorithm to solve the minimum value of the objective function, and optimize the immune algorithm through the aforementioned P-D-E resource optimization allocation strategy, IC population refresh optimization, and AMR mutation optimization. In the matlabR2018b compiler, the minimum value solution simulation was carried out with reference to the simulation conditions

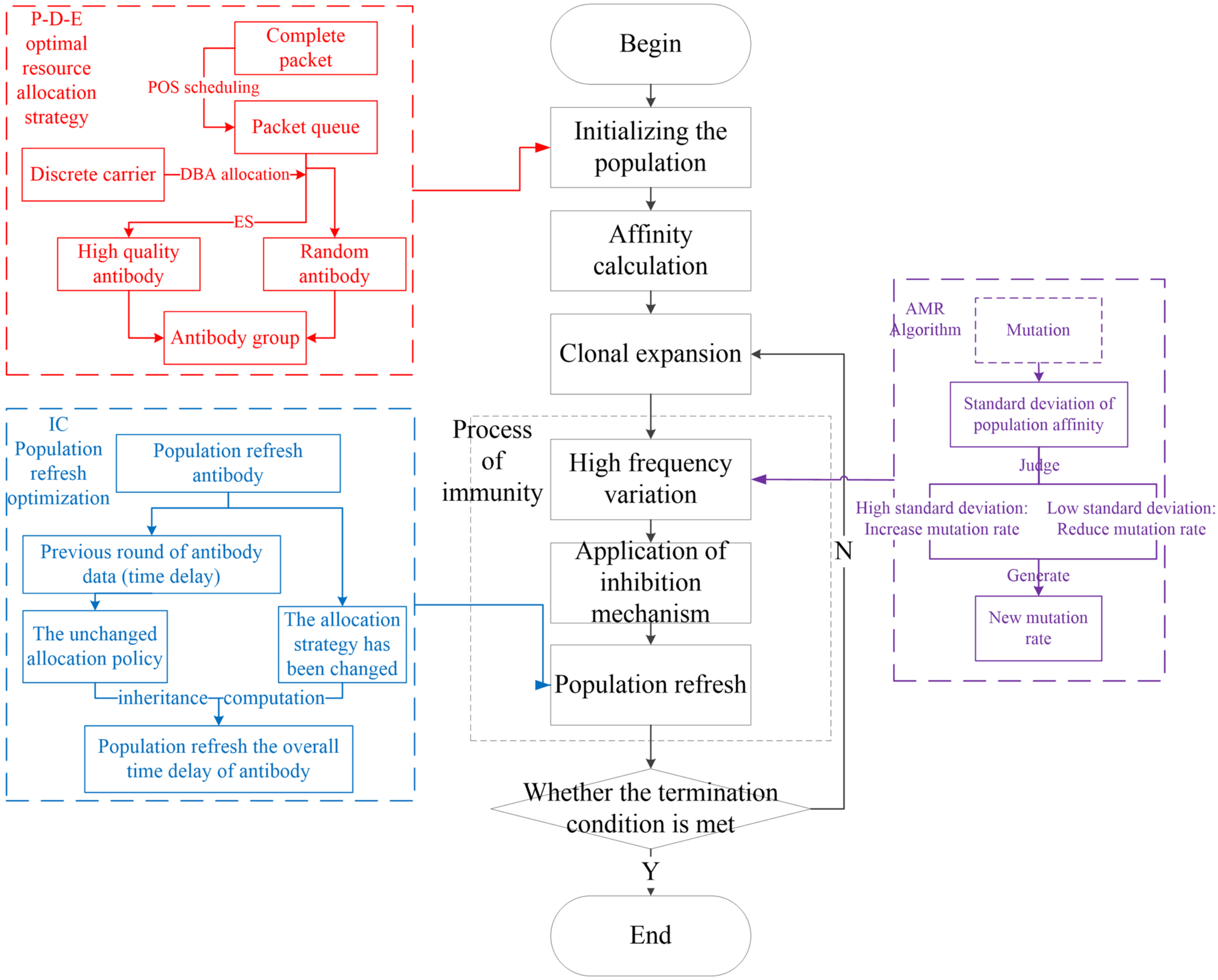



**Fig. 2.** The fast optimal value solving optimization strategy based on the immune algorithm.

in Table 1. The results of the minimum solution, the number of iterations and algebra, and the convergence rate are shown in Tables 2 and 3:

As shown in Table 2, under a 1 M bandwidth, it is considered to allocate resources through the discrete carrier aggregation method, dividing the content of data packets into three categories: precise control, utilization and acquisition, and power distribution. The number of data packets is simulated at 50,000. After seven generations of iteration, the algorithm can converge to the minimum value.

The scheduling strategies are presented in chronological order in Table 3. Among them, every 20ms is a TDD frame cycle, and the window scheduling is as follows: t = 0-20ms (the first cycle) : For the precision control class (10 users), 2 200 KHZ channels are allocated; For the first batch of 300 users, 16 25 kHz multiplexing channels will be used, with 18 people allocated to each channel. The distribution type idles and waits for the next cycle. t = 20-40ms (Period 2) : For distribution category (16 people), 2 100 kHz channels are used; Use the sampling class (the next batch of 300 users) to reuse the same 16 25 kHz channels again. The precise control type maintains the connection status as needed or rotates access. t = 40-60ms (Period 3) : Precise control for the scheduling of the next batch of users (or the continuation of the previous batch); The maintenance connection status of the power distribution category enters the reporting/idle cycle. Continue to rotate the next batch of data by reusing the spectrum resources of the acquisition type.

It can be known from Table 4 that after multiple repeated simulations, the average convergence algebra is 10 generations, the total average convergence speed is 8.2 s, and the average iteration time per generation is 0.82 s.

## Performance analysis and comparison

To demonstrate the effectiveness of the proposed method in mitigating severe packet blocking and delay under massive concurrent access, comparative experiments were conducted against several representative carrier allocation optimization approaches.We further considered algorithms that explicitly handle constrained resource allocation and packet queuing dynamics, including a Genetic Algorithm (GA) and an Ant Colony Optimization (ACO) method[23,24]. These algorithms were selected because they are widely applied in constrained combinatorial

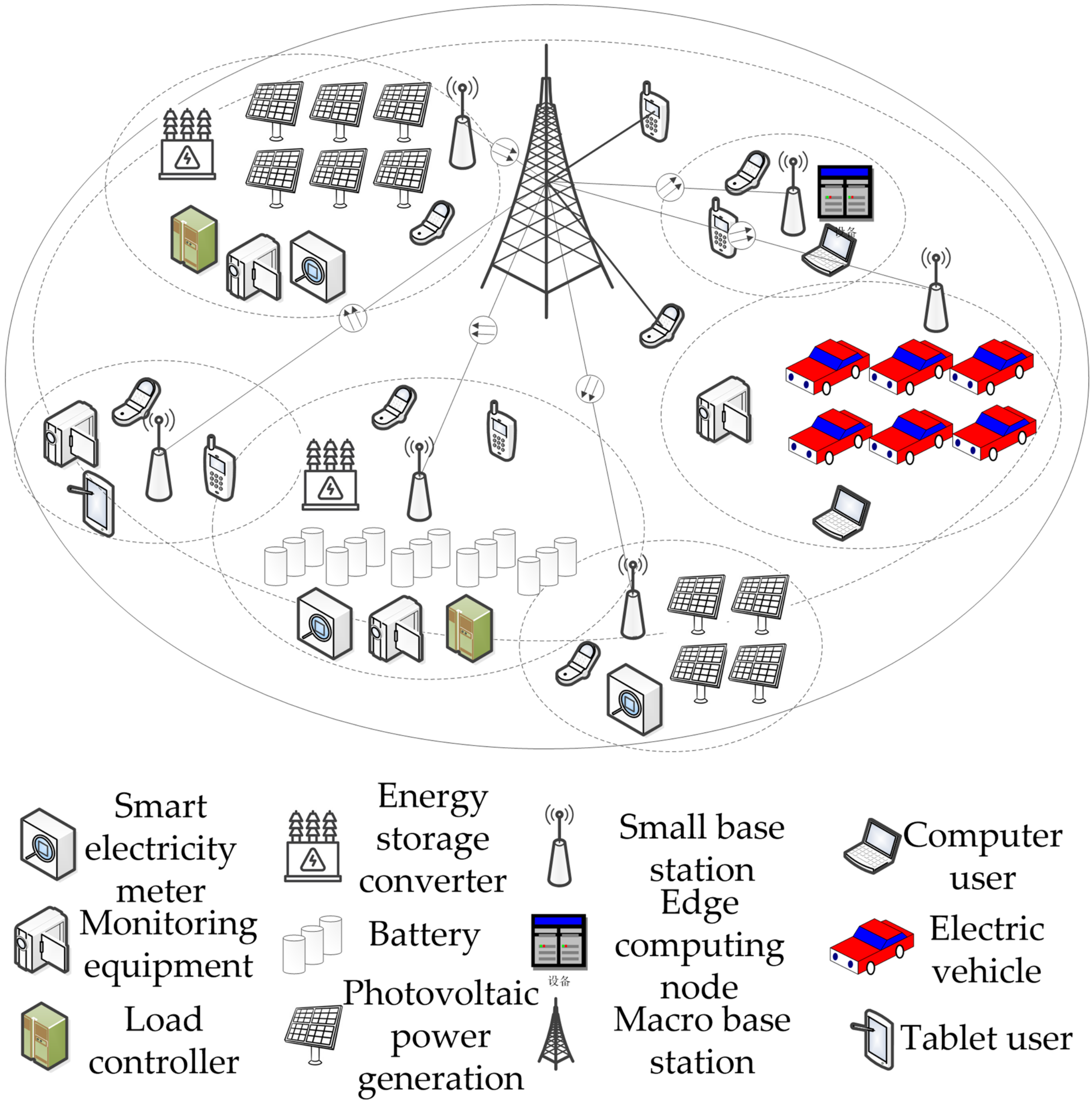



**Fig. 3**. The immune algorithm optimizes the solution process.

optimization and dynamic scheduling problems similar to the scenario studied in this work. The inclusion of GA and ACO strengthens the validation of the proposed immune algorithm by providing comparison with methods that share closer optimization mechanisms and constraint-handling capabilities.

As shown in Table 5; Fig. 5, the proposed AIA consistently outperforms all baseline algorithms in terms of average packet delay and packet loss rate, confirming its superior ability to achieve stable and efficient resource allocation under carrier and latency constraints.The results are as follows:

Figure 4 shows a 3D simulation diagram of iterative algebra - packet loss rate - number of packets. As can be seen from the graph, the packet loss rate is clearly higher in the early stages of the iteration than in the later stages; As the number of iterations gradually increases, although the packet loss rate increases significantly around the 8th generation, at this stage it may not be fully adapted to the sharp increase in the number of data packets, resulting in the delay processing of some low-priority or high-real-time small data packets, thereby increasing the risk of packet loss; The overall packet loss rate decreased with the increase in the number of iterations, possibly because the immune algorithm allocated resources better in the early stage by exploring the solution space, avoiding excessive competition or conflict; As the number of data packets increased, the rate of packet loss rose due to limited resources. As can be seen from the graph, the initial fitness values dropped rapidly, indicating that the algorithm was able to explore the solution space well at the beginning stage. The rate

| Bandwidth | 1 M, 40 subcarriers |
|---|---|
| Discrete carrier aggregation | 25 khz, 50 khz,<br>100 khz, 200 khz |
| Terminal height | 1.5 m |
| Business frequency point ratio | Distribution 10%, consumption and acquisition 80%, precision control 10% |
| Site height | The site is simulated at 30 |
| Number of packets | [0, 50,000] |
| Data packets | 1. Distribution Class: High real-time small data<br>2. Consumption category: Low real-time small data<br>3. Precision control category: High real-time big data |
| Precision negative control 48.1kpbs | 2.66 km |
| Use 2.5kbps | 6.92 km |
| Distribution: 19.2kbps | 3.88 km |

**Table 1**. Simulation conditions.

| Iterative algebra | Optimal affinity (minimum delay) | Iterative algebra | Optimal affinity (minimum delay) |
|---|---|---|---|
| 1 | 706.634286 | 18 | 672.314450 |
| … | … | 19 | 668.147178 |
| 3 | 706.634286 | … | … |
| 4 | 702.324432 | 34 | 668.147178 |
| … | … | 35 | 630.452701 |
| 12 | 702.324432 | … | … |
| 13 | 701.825998 | 40 | 630.452701 |
| … | … | 41 | 608.856071 |
| 15 | 701.825998 | … | … |
| 16 | 672.314450 | 100 | 608.856071 |
| … | … | | |

**Table 2**. Minimum value iteration results.

| Aggregate block frequency | Quantity (blocks) | Corresponding business | Single block of users | Total number of users | Total occupied bandwidth | Description of aggregation mode |
|---|---|---|---|---|---|---|
| 200 kHz | 2 | Precision control category | 5 | 10 | 400 | Allocate 2 exclusive 200 kHz blocks for 10 high real-time big data users |
| 100 kHz | 2 | Power distribution type | 8 | 16 | 200 | Eight people share a 100 kHz channel with a delay-sensitive medium rate |
| 25–50 kHz | 16 | usage classification | 15–20 | 240–320 | 400 | 25 kHz multiplexed channels, with each channel multiplexing 15 to 20 users |

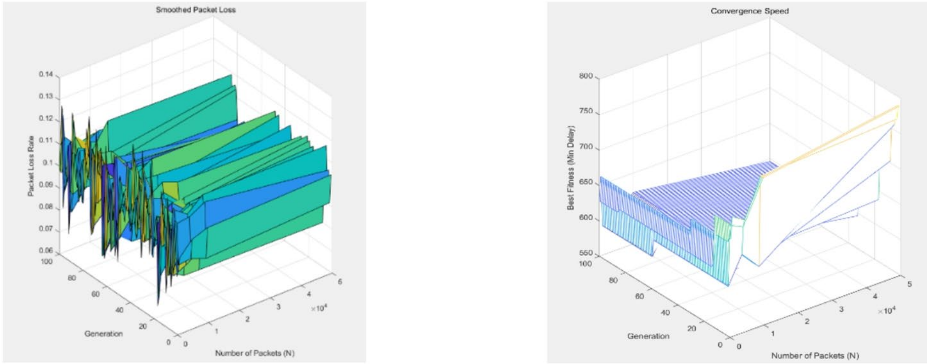
**Table 3**. The minimum iteration result of the proposed algorithm.

| Mean convergence algebra | Average total computation time | Average computing time per generation |
|---|---|---|
| 10 generations | 0.82270 s | 0.08223 |

**Table 4**. Convergence rate.

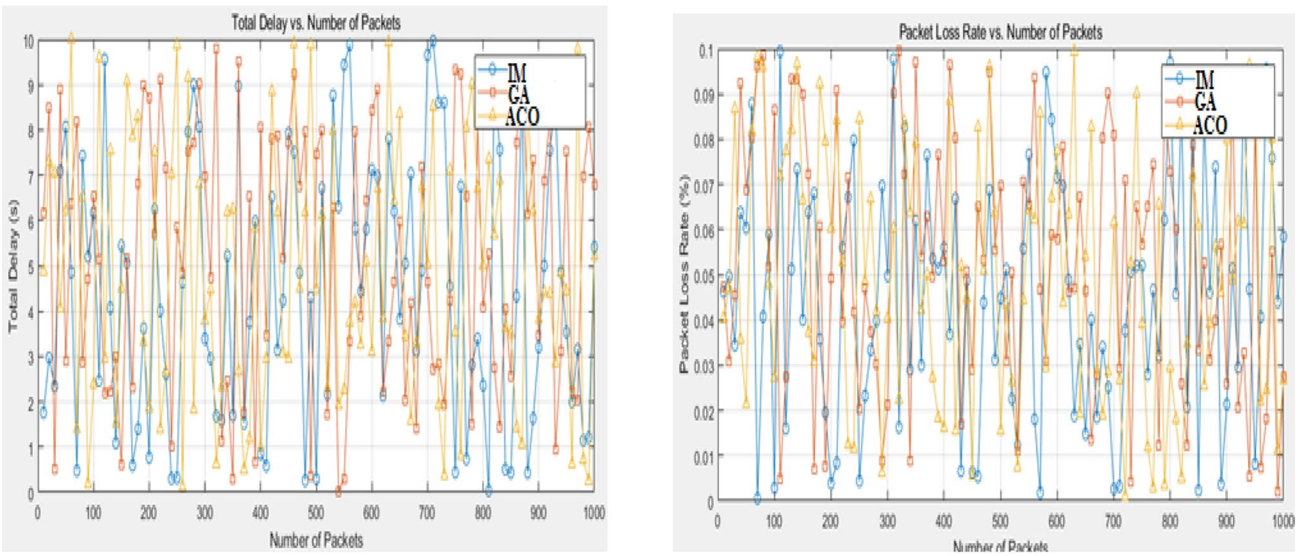
| | The proposed optimization method | GA algorithm | ACO algorithm |
|---|---|---|---|
| Average packet transport delay | 4.509198 s | 5.191268 s | 4.79353 s |
| Average packet loss rate | 4.54% | 5.28% | 5.00% |

**Table 5**. Comparison of algorithm performance. In addition to the average delay and packet loss rate, further performance indicators were analyzed to better evaluate the overall efficiency and stability of the proposed method. Specifically, fairness, jitter, and computational cost were introduced as supplementary metrics: Fairness was evaluated using Jain's fairness index, defined as:




(a) (b)

**Fig. 4**. 3D simulation diagram. (**a**) Cellular base station communication packet loss rate, (**b**) Algorithm convergence rate.




(a) (b)

**Fig. 5**. Performance as the amount of data increases simulation graph.

of fitness decline slows down in the middle stage, suggesting that the immune algorithm may have fallen into a local optimal solution. Later on, with further iterations of the algorithm, fitness drops rapidly again, gradually approaching the global optimal solution. As the number of data packets gradually increases, the changes in fitness in the graph tend to be more stable, possibly because more data packets introduce more resource contention and competition, resulting in a slower convergence rate.

Figure 5 shows the packet loss rate performance of the proposed algorithm and the other two algorithms as the number of data packets gradually increases. Combined with Table 4, it can be seen that the proposed algorithm has a better packet loss rate performance than the GA algorithm and the ACO algorithm, and is optimized by at least 0.5% points. Although the packet loss rate may be slightly higher in the medium term, in most cases, the proposed algorithm performs well in terms of packet loss rate.Combined with Table 5, it can be seen that the proposed algorithm performs better in data transmission than the GA algorithm and the ACO algorithm, improving the transmission time by at least 6%. The proposed algorithm has higher transmission delay in only a few cases, but in most cases, it performs well in terms of transmission time.

$$F = \frac{\left(\sum_{i} r_i\right)^2}{\left(n\sum_{i} r_i\right)^2} \tag{13}$$

where $r_i$represents the achieved transmission rate of user *i*. The proposed AIA achieved an average fairness index of 0.93, higher than 0.87 (ACO) and 0.85 (GA), indicating better balance among terminals.

Jitter was measured as the variance of end-to-end delay, which was reduced by approximately 11% compared with ACO, showing that AIA maintains more consistent transmission performance under varying load conditions.

Computational cost was evaluated in terms of average execution time per iteration. The AIA achieved 0.82 s per generation (Table 4), representing an approximate 35% reduction compared with ACO (1.26 s), mainly due to the incremental computation (IC) and adaptive mutation rate (AMR) strategies.

These additional analyses demonstrate that the proposed algorithm not only reduces delay and packet loss but also achieves higher fairness, lower jitter, and improved computational efficiency, confirming its overall superiority for real-time carrier allocation in power wireless private networks.

## Conclusion
This study investigates strategies for minimizing data packet transmission delay in the scenario of massive concurrent access in power wireless private networks. In the LTE system of the power wireless private network, when facing sudden massive concurrent access, packet loss and congestion caused by excessive data packets and data volume are severe, and the efficiency of the communication system drops sharply. To this end, under the constraint of 230 MHz, considering the diversity of data packet types and the discrete spectrum allocation strategy, with the goal of minimizing the overall delay of data packet transmission, a full data packet delay model and corresponding constraints for private cellular networking were established. To address the problems of getting stuck in local optimum and the inability of computing speed to meet real-time requirements in the carrier allocation constraint model of massive concurrent access data packets, P-D-E resource optimization allocation strategy, IC population refresh optimization strategy and AMR mutation optimization strategy were proposed, and the calculation process was detailed. Through the parallel optimization capability of the immune algorithm, the computing speed is significantly improved, ensuring the stability of data packet transmission in the case of limited carrier resources. The simulation results show that the proposed method has significant improvements in packet loss rate and data transmission time compared to the traditional GA algorithm and ACO algorithm in terms of data volume and packet type proportion during massive access. Specifically, the algorithm improves the average packet transmission delay by at least 6% and optimizes the average packet loss rate by at least 0.5% points.

## Discussion
Our AIA reduces average packet delay by 6% (4.51s vs. 5.19s) and packet loss by 0.5% (4.54% vs. 5.28%) versus GA/ACO (Table 5), demonstrating superior stability under massive access (e.g., post-power-restoration surges with 50k packets). Key advantages include:

1. 1.Real-Time Responsiveness: IC refresh enables 0.82s/generation computation (Table 4), critical for grid emergency scenarios.
2. 2.Adaptive Resource Allocation: P-D-E prioritizes high-real-time data (e.g., precision control), while AMR escapes local optima (Fig. 4b).

However, transient performance dips at ~8 iterations (Fig. 4a) indicate initial resource contention during exploration. Future work will:

Integrate LSTM-based traffic predictors to pre-allocate carriers before access surges.Extend to multi-base station clusters (beyond single-cell models) for large-scale deployment validation.

## Methods
P-D-E Initialization Strategy:

Priority Queue Scheduling (POS): Data packets are sorted by priority and size, ensuring high-priority/small packets (e.g., control commands) are scheduled first.
Dynamic Bandwidth Allocation (DBA): Critical packets receive larger discrete carriers ∈ {25,50,100,200} kHz, minimizing their transmission delay.
Elitism Strategy (ES): Top 20% high-affinity antibodies are preserved to accelerate convergence.
IC Population Refresh: Only modified scheduling segments (set *M_changed*) are recalculated, reusing 80% of prior iteration results to reduce computation by 5× (Table 4).
AMR Mutation: Adaptive mutation rate dynamically adjusts based on population diversity.

## Data availability
Data and supportive studies are contained within this article.

Received: 1 July 2025; Accepted: 22 October 2025
Published online: 29 October 2025

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## Author contributions

All authors have read and agreed to the published version of the manuscript.

## Declarations

## Competing interests

The authors declare no competing interests.

## Additional information

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