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GROUP INTELLIGENT CITY MOBILE COMMUNICATION NETWORK'S CONTROL STRATEGY BASED ON CELLULAR INTERNET OF THINGS

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Abstract. Mobile communication network optimization heavily depends on power control technology, which impacts the effectiveness of the network. This paper aims to enhance control over nonlinear mobile communication networks and achieve superior performance by applying the particle swarm optimization (PSO) algorithm in the control domain. Addressing limitations in the basic PSO algorithm, improvements are made and applied to urban mobile communication networks. The methodology involves modifying the PSO algorithm to address identified issues and applying the enhanced algorithm to communication network scenarios. Simulation results indicate that with an initial particle count of 10 and 100 iterations, the optimized values for and are 0.691 and 0.486, respectively, resulting in an objective function value of 55.514. This achievement validates the successful implementation of the optimization process for mobile communication network control. The findings reveal that the proposed grad particle swarm optimization (Grad-PSO) algorithm exhibits mobile network optimization by robust search capability and rapid convergence.

Key words: Grad-PSO, Particle movement, Mobile communication network, Optimal control, Internet of Things (IoT), Learning factors.

1. Introduction.

Mobile communication technology is undergoing profound transformations due to the swift advancement of intelligent appliances and the Internet of Things. Primarily, mobile communication is controlled to sustain a rapid developmental pace regarding user count and overall service. According to the International Telecommunication Union (ITU), the tally of mobile subscribers reached nearly 7 billion by the close of 2014, with mobile broadband's growth rate consistently in the double digits. The surging demand for mobile communication network technology presents significant opportunities and challenges, fueling a surge in research and development across academic and industrial sectors, focusing on novel services, technologies, standards, and products [1].

Within this dynamic context, 5G has emerged as a prominent focal point of communication technology's evolution, demonstrating extensive application prospects. Mobile communication network users are surging, business domains are expanding, and network equipment is diversifying extensively. It compels mobile communication networks to enhance the provision of diverse services to an expanding user base, all while upholding communication quality. Consequently, the prerequisites for mobile communication-related technologies are escalating distinctly. The pivotal technology within mobile communication networks efficiently mitigates the power control technology by direct interference among users operating on adjacent or near channels due to the "far and near effect." This substantial enhancement strengthens mobile communication networks' capacity and quality [2].

The Internet of Things (IoT) is a pivotal driving force for the evolution of mobile communications. Mobile Internet has revolutionized conventional mobile communication services, furnishing users with experiences such as ultra-high definition (3D) video, augmented and virtual reality, mobile cloud, and other immersive, cutting-edge ventures. It has spurred a comprehensive metamorphosis in the information interaction mode, speeding up the rapid maturation of mobile communication technology and the industry [3].

Moreover, the IoT has expansively broadened mobile communication applications. This expansion transcends interpersonal communication, spanning into intelligent interconnections between various objects, facilitating the application of mobile communication technology across various industries and sectors. The spread of IoT

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applications, ranging from mobile healthcare and smart homes to industrial control, vehicular networking, and environmental monitoring, will manifest in greater abundance [4].

The profound vision of an interconnected world, termed "the Internet of Everything," is controlled to materialize as an extensive array of IoT devices interface with the network for diverse purposes. This surge in IoT-driven applications has given rise to many emerging industries, thus catalyzing the robust advancement of mobile communication technology and the industry. Against this "Internet of Everything" demand, the pressing need for massive device connectivity, diverse services, and distinct user experiences has emerged as new focal points for mobile communication research. Regarding the challenge of power control within mobile communication networks, scholars worldwide have undertaken extensive research, applying an extent of optimization algorithms to address this issue. While algorithms like genetic, ant colony, and particle swarm optimization methods have made strides in resolving power control problems, their shortcomings, namely sluggish convergence, modest precision, and susceptibility to local optimization, adversely impact real-time performance and accuracy. In response to these challenges and aligning with the IoT's stipulations for high reliability, low latency, and reduced energy consumption, incorporating cache resources within the IoT is paramount in efficiently managing the escalating IoT traffic [5, 6].

The paper's section organization follows a structured progression to investigate the control method for group intelligent city mobile communication networks using the Cellular Internet of Things (CIoT). The literature review surveys relevant aspects of mobile communication networks, CIoT, and swarm intelligence algorithms are discussed in Section 2. The proposed methodology outlines the proposed control approach, integrating PSO within CIoT, explained in Section 3. The simulation and results are demonstrated in Section 4, which details the method's effectiveness through experimental comparisons and performance analysis. The conclusion summarizes findings, contributions, and implications, emphasizing the significance of the research in shaping the future of group intelligent city networks based on cellular IoT.

2. Literature review. Many experts and scholars have exhibited a pronounced interest in swarm intelligence, delving into novel approaches to tackle conventional intricate quandaries. Their pursuit involves scrutinizing social insects' societal conduct, precisely, the collaborative food-finding endeavours of simple insects. Rooted in swarm intelligence, these diligent minds have introduced an array of algorithms, with the ant colony algorithm and PSO emerging as the most emblematic exemplars [7].

The PSO algorithm was introduced by Kennedy and Eberhart in 2000, drawing inspiration from the seeking behaviours of birds. It has evolved into a strong tool for nonlinear continuous optimization, combinatorial optimization, mixed-integer nonlinear optimization, and various other optimization challenges due to its straightforward process, limited parameter requirements, simple algorithmic structure, and ease of implementation. Nevertheless, nonlinear PSO possesses shortcomings such as insensitivity to environmental changes and susceptibility to local minima. In recent years, scholars have devised enhanced algorithms grounded in nonlinear PSO. Key advancements encompass parameter tuning, particle diversity selection, population structure determination, and amalgamation with other intelligent techniques. Relative to counterparts like ant colonies and genetic algorithms, PSO's advantage lies in its fewer adjustable parameters; however, their meticulous selection significantly influences accuracy and efficiency [8].

Three universally applicable principles are introduced for selecting population size, iteration count, and particle velocity to enhance nonlinear PSO's effectiveness. Additionally, experts have incorporated PSO with other methods to overcome the local optima problem through population diversity control, balancing particle attraction and repulsion processes. Further innovations include an adaptive PSO to navigate spatial changes in dynamic systems, along with Qiu's modulation strategy for mobile communication systems [9].

The theoretical foundation for PSO enhancements and applications remains underdeveloped. Particle swarm optimization parameters are confined mainly to experimental realms, lacking comprehensive and well-defined understanding. Therefore, exploring nonlinear particle swarm algorithms holds profound importance for comprehending their internal mechanics and expanding their scope. Cellular networks have evolved as a foundation in mobile communications, offering extensive coverage and reliable communication. Projections by Qualcomm indicate that global IoT connectivity will surpass 5 billion by 2025, around diverse applications from wearable devices to environmental monitoring. The propagation of intelligent devices connecting to cellular networks positions them as the primary infrastructure for the Internet of Things [10].

The enhancement and practical utilization of the PSO algorithm suffer from a shortage of theoretical robustness. Parameters within the PSO algorithm remain within experimental realms, lacking substantial and well-defined conceptualization. Thus, as an emerging intelligence paradigm, the nonlinear particle swarm algorithm is essential for investigating its intrinsic mechanisms and expanding its application spheres. This IoT growth extends across smart cities, transportation, environmental monitoring, and medical care, encompassing an array of facets, from intelligent wearables and water/electricity meters to smart infrastructure like utility hole covers and vehicular terminals. As such, many intelligent endpoints will interface with the network, thus establishing cellular networks as the primary backbone for the Internet of Things [11].

The authors focus on crafting and executing machine learning methodologies to enhance smart cities' data processing efficiency, decision-making, and resource management capabilities. The research is anticipated to explore a range of machine learning algorithms, including neural networks, support vector machines, clustering, and deep learning models. These techniques can be analyzed for their potential utility across intelligent city domains such as traffic management, energy optimization, waste management, public safety, and healthcare [12].

This study conducts an exhaustive survey on the potential applications of utilizing 5G network-based IoT for demand response within smart grids. The investigation scrutinizes how this innovative strategy can augment grid efficiency and responsiveness, contributing to a more sustainable and adaptable energy ecosystem. The research gap becomes evident in the need for an all-encompassing, interdisciplinary approach that bridges the theoretical prospects of 5G network-based IoT for demand response in smart grids with tangible considerations, economic feasibility, regulatory hurdles, and human-centred aspects. Such an approach would yield a more comprehensive grasp of the authentic potential, limitations, and prerequisites essential for effectively merging these technologies, ultimately shaping the future energy management trajectory [13].

An adequate examination of the pragmatic challenges and constraints of deploying such a system within intricate and dynamic urban settings is lacking. Despite proposing an inventive IoT-based method for accident detection and reporting in smart cities, the study frequently neglects potential hindrances associated with real-world implementation. Fundamentally, although the envisioned IoT-powered accident detection and reporting system exhibits potential, additional research is imperative to bridge the disparity between theoretical concepts and pragmatic complexities. This endeavour is essential to ensure the system's efficacy, dependability, and smooth adjustment within smart city environments [14].

The research fails to thoroughly examine the challenges and constraints of merging big data analysis and deep learning techniques for constructing digital twins in smart cities. Although the suggested approach exhibits potential for supporting smart city planning via digital twins, additional research is imperative to tackle the noted deficiencies. This encompasses comprehending hurdles in data integration, ensuring model adaptability, considering resource ramifications, fostering interdisciplinary collaboration, and addressing ethical considerations. Addressing these gaps will play a pivotal role in harnessing the full potential of big data analysis and deep learning for the inception and application of digital twins in smart urban environments [15].

3. 3.Proposed Grad-Particle Swarm Optimization algorithm. The PSO algorithm characterizes each solution within an optimization problem as a "particle." The fitness values of these particles derive from the objective function under optimization. Furthermore, individual particles possess velocities, prompting them to trail the presently optimal particle across the solution space during the iterative search until the ultimate solution surfaces.

Figure 3.1 illustrates the optimal control flowchart for a group-intelligent mobile communication network founded upon the cellular IoT paradigm. Each particle refines its position by monitoring two "extremes" throughout each iteration. The particle's self-derived optimal solution is termed the individual extremum. p_{best} While the prevailing optimal solution for the entire population is known as the global extremum g_{best} Particles must continually update both their velocity and position, a process governed by Equations 3.1 and 3.2.

$$v_i = \omega v_{i-1} + c_1 \times r_1 \times [p_{best} - x_{i-1}] + c_2 \times r_2 \times [g_{best} - x_{i-1}] \tag{3.1}$$

$$x_i = x_{i-1} + v_i \tag{3.2}$$

In the context of this representation, v_i and v_{i-1} stand for the current and preceding particle movement speeds, correspondingly. Likewise, x_i and x_{i-1} denote the current and former particle positions, respectively. The

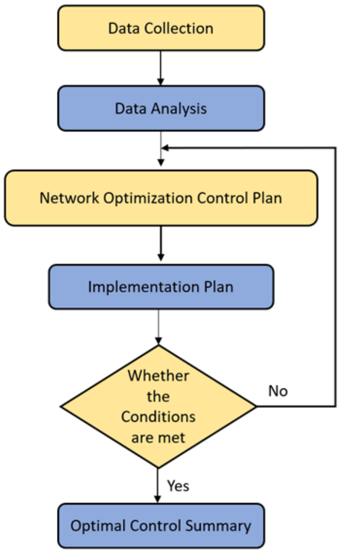

Fig. 3.1: Flowchart for a group-intelligent mobile communication network

symbol ω signifies inertial weights, while p_{best} and g_{best} Indicate individual and global extrema, respectively. The parameters c_1 and c_2 encapsulate learning factors, typically adopting equal values like $c_1 = c_2 = 2$. Furthermore, r_1, r_2 are random numbers spanning the range from 0 to 1.

By amalgamating the operational swiftness and precision benefits inherent in traditional value optimization techniques, a novel approach seeks to enhance the convergence velocity of the PSO algorithm. To this end, the gradient method is infused into the PSO framework, culminating in a Grad-PSO algorithm fortified by a gradient search factor. This algorithm posits the existence of a global minimum for the optimization function within the domain space . It envisions a circular region "A," centred at the global minimum "g," and circumscribed by a radius "r," representing the optimal zone.

During particle movement, when far from the global optimal value, the original position updating strategy of the PSO algorithm is retained. In contrast, the gradient method governs position updates when proximity to the global optimum is achieved. This strategic integration alleviates the computational burden introduced by the stochastic particle position updates within the PSO algorithm. Upon entering the optimal region, the gradient method guides particles to converge towards the optimal position swiftly, amplifying the optimization pace.

While introducing the gradient method compromises some of the PSO algorithm's randomness and adaptability, it ensures particles within the optimal region remain confined, heightening single optimization efficiency. Consequently, the overall optimization efficiency of the algorithm is markedly enhanced. The specific velocity and position updating mechanism of the Grad-PSO algorithm is articulated through Equations 3.3 to 3.4.

$$x = x + v, f(x) > f(g) + r \tag{3.3}$$

$$x = T(x), f(x) \leqslant f(g) + r \tag{3.4}$$

To verify the advantages of the proposed Grad-PSO algorithm, the following mathematical problems are analyzed. The target function is $minf(x) = x^2 + 2x + 6$. The constraint is $-10 \leqslant x \leqslant 10$. The problem is optimizing one variable function with boundary constraints [16]. The global optimal solution is $f(x) = 5.0000$. Matlab is used for programming, and the simulation results are shown in Figure 3.2.

The simulation experiment yields evidence that the Grad-PSO algorithm exhibits enhanced regularity within the optimization function, owing to the incorporation of the gradient search factor. This characteristic

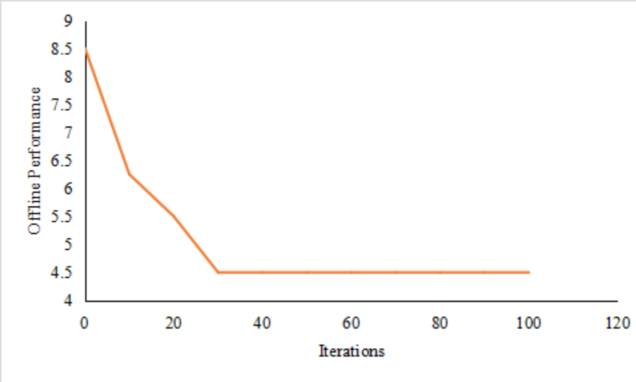

Fig. 3.2: Simulation result of optimization function of Grad-PSO algorithm

demonstrates heightened optimization efficiency and remarkable precision. In summation, it can be deduced that the Grad-PSO algorithm is a notably superior approach to function optimization. Within CDMA technology-based cellular mobile communication systems, user terminals employ a shared spectrum for uplink and downlink data transmission, inevitably leading to user interference. A prominent illustration is in broadband CDMA cellular mobile communication systems, characterized by the "near and far effect." This effect is intimately linked with channel power during user communication. Thus, effective management of the signal power of user terminals is essential to mitigate this phenomenon.

Furthermore, optimizing the transmission power of base stations plays a pivotal role. This optimization ensures that each user terminal receives an appropriate radiated power from the base station, contributing to improved overall system performance. In a mobile communication system, the capacity and efficiency of frequency spectrum utilization are directly contingent upon each user's signal power and transmission rate. A comprehensive mathematical model is devised to address power control challenges within mobile communication networks, accounting for the interplay between power control and rate control strategies.

Consider a multi-cell DS-CDMA cellular mobile communication system comprising N users, collectively sharing a spread bandwidth denoted as W. Notably, each user imposes distinct requisites concerning transmission rate, delay, and bit error rate. For analytical convenience, let's define the maximum allowable transmission power per user as P_{maxi} alongside the minimum required transmission rate denoted as R_{mini}. In addition, a designated target bit energy-to-noise ratio $(E_b/N_0)$is selected to align with specific bit error rate criteria. This enables incorporating a variable transmission rate within a predetermined range to cater to individual user-imposed delay constraints.

Integral to this model is the representation of critical factors. The parameter h_{ii} captures the channel gain from user "i" to the receiver at its base station. Similarly, h_{ij} signifies the channel gain originating from user "j" to the receiving base station of user "i." The signal transmission power of user "i" is denoted as P_i or γ_i aligned with the target E_b/N_0 requirement. Additionally, the background noise encountered at the base station receiver assumes an additive white Gaussian nature, characterized by a unilateral power spectral density of η_0. Central to this framework is the normalized signal-to-noise ratio at the base station, conveyed as E_b/N_0. The illustration of this scenario is encapsulated within Equation 3.5, showcasing the reception of the user signal by the base station.

$$\frac{E_b}{N_0} = \frac{W}{R_i} \cdot \frac{h_{ii} \times P_i}{\sum\limits_{i \neq j} h_{ij} \times P_j + \eta_0 \times W} \tag{3.5}$$

$$i = 1, 2, 3, ..., N \tag{3.6}$$

To moderate interference among users in different cells, optimization is pursued through the minimization of total transmitted power. Addressing scenarios where the system is congested and quality of service requirements must be upheld, a priority control strategy is introduced as follows: With a commitment to maintaining high-priority services, the strategy endeavours to augment the transmission quality of low-priority services. This augmentation is achieved by carefully elevating transmission power. To organize user priorities, a coefficient A_i is introduced [17]. The optimization problem's objective function is formulated in Equation 3.6, while the constraints are articulated through Equations 3.7 to 3.9.

$$\min \sum A_i P_i \tag{3.7}$$

$$\frac{E_b}{N_0} \geqslant \gamma_i \tag{3.8}$$

$$0 \leqslant P_i \leqslant P_{maxi} \tag{3.9}$$

$$R_i \geqslant R_{mini} \tag{3.10}$$

The evaluation of the objective function's values throughout various iterations evaluates the algorithm's advancement and its rate of convergence. This iterative process of enhancement, guided by the objective function, amplifies the algorithm's effectiveness in addressing complex problems.

4. Results and Discussion. To simplify the calculation, the mathematical model is simplified, starting from a relatively simple case N=2. Set up N=2, i=1,2, $P_1 = x_1, P_2 = x_2, R_1 = y$. According to the actual situation of the mobile communication network, set $W = 100MHz$, $\eta_0 = 2 \times 10^{-8}, h_{11} = 2, h_{12} = 3, h_{21} = 1.5, h_{22} = 2.5, \gamma_i = 0.8, P_{max1} = P_{max2} = 1W, R_{mini} = 50Kb/s$ weight coefficient $A_1 = 30, A_2 = 100$. The grad-PSO algorithm is used to optimize the power control. Its objective function is shown in Equation 4.1, and its constraint conditions are shown in Equations 4.2-4.3.

$$f(x_1, x_2) = min(30x_1 + 100x_2) \tag{4.1}$$

$$\frac{200x_1}{y(3x_2+2)} \geqslant 0.8 \tag{4.2}$$

$$\frac{250x_1}{y(1.5x_2+2)} \geqslant 0.8 \tag{4.3}$$

where $0 \leqslant x_1 \leqslant 1; 0 \leqslant x_2 \leqslant 1; y \geqslant 50$.

The specific processing flow of the Grad-PSO algorithm is as follows.

Step 1: Set each parameter of the algorithm, such as the number of particles contained in the population, that is the size of the population . Coefficient of inertia weight $\omega = 0.9$ and acceleration constants $c_1 = c_2 = 2$.

Step 2: Perform arbitrary initialization on the particles of the population (the population size is N), and calculate and determine the fitness of all particles;

Step 3: Evaluate the fitness of each particle calculated in step 2;

Step 4: Match the fitness value of each particle with the historical best position the comparison was performed. If the current particle fitness value is better, thenis updated to the current fitness value;

Step 5: For each particle, the fitness value of fitness is combined with the historical optimal position of the population g_{best}. If the best fitness value in the current population is better than the historical best g_{best}. Then update it to g_{best}.

Step 6: Update the position and velocity of each particle according to the formula;

Step 7: Calculate the performance index to see whether it meets the optimization end condition. If the condition is met, the current result is the optimal solution, and the algorithm ends. Otherwise, return to Step 3 and continue the next loop.

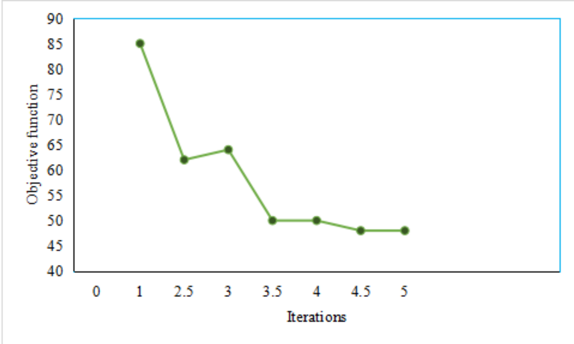

Fig. 4.1: Objective function when the initial particle number is 10

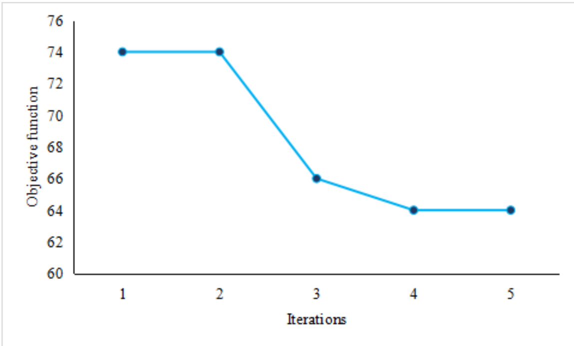

Fig. 4.2: Objective function when the initial particle number is 20

By applying the grad-PSO algorithm to solve the objective function, the optimal solution can be obtained as $x_1 = 0.6916, x_2 = 0.4860$. The target function is zero for $f = 55.5140$. Figures 4.1 and 4.2 show the changes and comparison of the offline performance curve of the Grad-PSO algorithm when the number of iterations is five, and the initial particle number is 10 and 20.

Upon comparing Figure 4.1 and Figure 4.2, it becomes evident that the Grad-PSO algorithm exhibits disparate convergence speeds and paths while undergoing the same number of iterations but with varying initial particle quantities. However, it's noteworthy that, ultimately, both scenarios attain an identical optimal solution.

Table 4.1, presented below, illustrates the shifts in particle optimal positions (x_1, x_2) and objective function value (f) with changes in iteration count for initial particle numbers 10 and 20, respectively. The data in Table 4.1 demonstrates that as the iteration count escalates, the Grad-PSO algorithm progressively approaches the optimal value, remaining resilient against divergence from the optimal solution due to inherent randomness. Despite their distinct initial particle counts, the convergence trajectory and pace vary under equivalent iteration counts. Nonetheless, both scenarios efficiently converge towards the optimal power control objective, swiftly realizing the optimization of the power control function.

5. Conclusion. This paper explored the power control principles that lead to a simplified model, viewed through the lens of joint power and rate control. The Grad-PSO algorithm, a typical group intelligence technique, finds wide application in engineering optimization challenges. Implementing the Grad-PSO in mobile communication networks enhances blind channel equalization and communication quality. The Grad-PSO algorithm claims discontinuity and differentiation, powerful search capabilities, and rapid convergence rates. As particle count rises, so does the likelihood of achieving optimal solutions. Simulations demonstrate that with an initial particle count of 10 and 100 iterations, x_1 attains 0.691, x_2 reaches 0.486, and the objective function

Table 4.1: Particle optimal position and objective function values with the number of iterations

Initial number of particles	10				20			
Number of iterations	5	20	40	100	5	20	40	100
x_1	0.782	0.693	0.691	0.691	0.811	0.691	0.691	0.691
x_2	0.416	0.488	0.486	0.486	0.547	0.486	0.486	0.486
f	59.441	55.757	55.517	55.514	62.892	55.561	55.515	55.514

value stands at 55.514, ultimately securing an optimal solution and enabling effective mobile communication network control. Furthermore, as the PSO algorithm refines its iterative processes, the probability of rapid optimal solution attainment surges.

REFERENCES

[1] Zhao, Y., Yu, G., & Xu, H. (2019). 6G mobile communication network: vision, challenges and key technologies. arXiv preprint arXiv:1905.04983.

[2] Ni, Y., Liang, J., Shi, X., & Ban, D. (2019, January). Research on key technology in 5G mobile communication network. In 2019 International Conference on Intelligent Transportation, Big Data & Smart City (ICITBS) (pp. 199-201). IEEE.

[3] Jeong, Y. S., & Park, J. H. (2019). IoT and smart city technology: challenges, opportunities, and solutions. Journal of Information Processing Systems, 15(2), 233-238.

[4] Elazhary, H. (2019). Internet of Things (IoT), mobile cloud, cloudlet, mobile IoT, IoT cloud, fog, mobile edge, and edge emerging computing paradigms: Disambiguation and research directions. Journal of network and computer applications, 128, 105-140.

[5] Zhang, H., Shlezinger, N., Guidi, F., Dardari, D., Imani, M. F., & Eldar, Y. C. (2022). Near-field wireless power transfer for 6G internet of everything mobile networks: Opportunities and challenges. IEEE Communications Magazine, 60(3), 12-18.

[6] Liu, Y., Dai, H. N., Wang, Q., Shukla, M. K., & Imran, M. (2020). Unmanned aerial vehicle for internet of everything: Opportunities and challenges. Computer communications, 155, 66-83.

[7] Gupta, A., & Srivastava, S. (2020). Comparative analysis of ant colony and particle swarm optimization algorithms for distance optimization. Procedia Computer Science, 173, 245-253.

[8] Yu, M. (2019). A solution of TSP based on the ant colony algorithm improved by particle swarm optimization. Discrete and Continuous Dynamical Systems-S, 12(4&5), 979-987.

[9] Zhang, X., Jia, M., Chen, L., Ma, J., & Qiu, J. (2015, December). Filtered-OFDM-enabler for flexible waveform in the 5th generation cellular networks. In 2015 IEEE global communications conference (GLOBECOM) (pp. 1-6). IEEE.

[10] Bello, O., & Zeadally, S. (2014). Intelligent device-to-device communication in the internet of things. IEEE Systems Journal, 10(3), 1172-1182.

[11] Pasolini, G., Buratti, C., Feltrin, L., Zabini, F., De Castro, C., Verdone, R., & Andrisano, O. (2018). Smart city pilot projects using LoRa and IEEE802. 15.4 technologies. Sensors, 18(4), 1118.

[12] Din, I. U., Guizani, M., Rodrigues, J. J., Hassan, S., & Korotaev, V. V. (2019). Machine learning in the Internet of Things: Designed techniques for smart cities. Future Generation Computer Systems, 100, 826-843.

[13] Hui, H., Ding, Y., Shi, Q., Li, F., Song, Y., & Yan, J. (2020). 5G network-based Internet of Things for demand response in smart grid: A survey on application potential. Applied Energy, 257, 113972.

[14] Bhatti, F., Shah, M. A., Maple, C., & Islam, S. U. (2019). A novel internet of things-enabled accident detection and reporting system for smart city environments. sensors, 19(9), 2071.

[15] Li, X., Liu, H., Wang, W., Zheng, Y., Lv, H., & Lv, Z. (2022). Big data analysis of the internet of things in the digital twins of smart city based on deep learning. Future Generation Computer Systems, 128, 167-177.

[16] Yazdanpanah, F. , Afsharmazayejani, R. , Alaei, M. , Rezaei, A. , & Daneshtalab, M. . (2019). An energy-efficient partition-based xyz-planar routing algorithm for a wireless network-on-chip. Journal of supercomputing, 75(2), 837-861.

[17] Sun, B. , Ding, J. , Lin, S. , Wang, W. , Chen, Q. , & Zhong, Z. . (2019). Comparison analysis on feasible solutions for LTE based next-generation railway mobile communication system. ZTE Communications, 17(01), 60-66.

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