A Novel Sensor Task Allocation Method Based on Quantum Elite Shuffled Frog Leaping Algorithm in IWSNs

Jing Xiao\textsuperscript{1a}, Yang Liu\textsuperscript{1b}, Yao Zhang\textsuperscript{3c}, Jie Zhou\textsuperscript{1,2, *}, Chaoqun Li\textsuperscript{1d} and Rui Yang\textsuperscript{1e}

\textsuperscript{1}College of Information Science and Technology, Shihezi University, Shihezi, 832000, China
\textsuperscript{2}Xinjiang Tianfu Information Technology Co., Ltd
\textsuperscript{3}University of the Cordilleras, Baguio City 2600, Philippines

\textsuperscript{a}xj_inf@shzu.edu.cn, \textsuperscript{b}liuyang@stu.shzu.edu.cn, \textsuperscript{c}y-z7247@students.uc-bcf.edu.ph, \textsuperscript{d}jiezhou@shzu.edu.cn, \textsuperscript{e}chaoqunli@stu.shzu.edu.cn, \textsuperscript{*}20192008001@stu.shzu.edu.cn

Abstract. Maximizing the efficiency of sensor task allocation has long been a question of great interest in industrial wireless sensor networks (IWSNs). In IWSNs, different tasks performed by different sensors produce varied benefit values. The purpose of this paper is to obtain the optimal task allocation scheme of IWSNs. Therefore, we design a sensor task allocation model, and propose a quantum elite shuffled frog leaping algorithm (QES-FLA) for optimizing the task allocation in IWSNs. The proposed algorithm combines the quantum operator and elite operator to achieve better performance. By using the concept of quantum probability amplitude and quantum revolving gate, the algorithm can search the solution space in parallel, thus enhancing the efficiency of solving the task allocation problem in IWSNs. In addition, the elite operator keeps the optimal individual in the population, which ensures the performance of the algorithm. Subsequently, the proposed algorithm is compared with two other popular heuristic algorithms to make the conclusion more convincing. According to the simulation results, the algorithm we proposed has higher task benefits and better performance, thus it successfully solves the sensor task allocation problem in IWSNs.

Keywords: sensor network, task allocation, shuffled frog leaping algorithm

1. Introduction
Developed on the basis of wireless sensor networks (WSNs), the industrial wireless sensor networks (IWSNs) integrate the concepts of Industry 4.0 and the Internet of Things, and it plays an increasingly important role in industrial automation applications [1, 2]. Compared with ordinary wireless sensor networks, IWSNs have the characteristics of high real-time requirements and complex working environment [3]. Therefore, many advantages of IWSNs are produced, such as convenience, controllability and timeliness.

Sensor task allocation is a key problem in IWSNs [4]. Due to the difference in sensor monitoring capabilities and work efficiency, different tasks performed by different sensor nodes have varied monitoring advantage values. In IWSNs, the optimal task allocation strategy requires exhaustive search of the entire solution space, which will bring large complexity of computation. Therefore, as an NP-hard problem, many studies have proposed approaches for obtaining an optimal solution of sensor task allocation [5-7].
In [8], the authors use genetic algorithm (GA) to solve the sensor task allocation problem. GA can get an acceptable solution, but it is more likely to fall into a local optimum, and the selection of genetic algorithm parameters seriously affects the quality of the solution. From another aspect, paper [9] proposes an improved simulated annealing algorithm for reducing the complexity on solving the task allocation problem. However, the simulated annealing algorithm has the disadvantages of long execution time and slow convergence speed. With the purpose of accelerating the process of solving the task allocation problem, paper [10] puts forward an improved particle swarm algorithm, which can get a low-energy and high-efficiency task allocation scheme, but the algorithm lacks the consideration of the global search ability, and has the probability of falling into premature.

In this paper, to better describe the problem, we first give the mathematical model of the sensor task allocation. Subsequently, we propose a quantum elite shuffled frog leaping algorithm (QES-FLA), which uses the quantum probability amplitude in quantum computing for enhancing the global search ability and applies the elite strategy to improve the convergence performance of the algorithm.

To make the conclusion more convincing, we compare the proposed algorithm with two current popular heuristic algorithms, one is simulated annealing (SA) algorithm and another is particle swarm optimization (PSO) algorithm. According to the simulation results, the proposed algorithm obtains higher task allocation benefits and faster convergence speed than that of SA and PSO.

2. System Model

In this section, to solve the sensor task allocation problem in IWSNs, we establish the mathematical model. Suppose there are \( n \) sensors in the IWSNs system and \( m \) tasks are waiting to be assigned. The urgency and the advantage value of each task performed by the sensor have been evaluated in advance.

The task urgency matrix \( E \) is shown in equation (1).

\[
E = \begin{bmatrix}
e_1 & e_2 & \cdots & e_i & \cdots & e_m 
\end{bmatrix}
\]

where \( m \) is the quantity of tasks, \( e_i \) represents the urgency value of the \( i \)-th task.

The advantage matrix \( X \) of the task performed by the sensor is shown in Equation 2.

\[
X = \begin{bmatrix}
x_{1,1} & x_{1,2} & \cdots & x_{1,M-1} & x_{1,M} \\
x_{2,1} & x_{2,2} & \cdots & x_{2,M-1} & x_{2,M} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
x_{N-1,1} & x_{N-1,2} & \cdots & x_{N-1,M-1} & x_{N-1,M} \\
x_{N,1} & x_{N,2} & \cdots & x_{N,M-1} & x_{N,M}
\end{bmatrix}
\]

where \( N \) refers to the quantity of sensors, \( M \) is the quantity of tasks, and \( x_{n,m} \) represents the advantage value generated by the \( n \)-th sensor performing the \( m \)-th task.

Equation (3) is the calculation formula for the benefit value of the sensor performing the task.

\[
b_{c,d} = e_d \times x_{c,d} \quad (c \in [1, N], d \in [1, M])
\]

where \( b_{c,d} \) stands for the benefit value of the \( c \)-th sensor performing the \( d \)-th task.

In IWSNs, the purpose of sensor task allocation is to pursue the maximum benefit value while meeting the basic requirements of the allocation. Therefore, the objective function in the model is shown in equation (4).

\[
obj = \max\left( \sum_{d=1}^{M} b_{c,d} | c \in [1, N] \right)
\]

In (4), \( M \) represents the quantity of tasks, \( N \) denotes the quantity of sensors, and \( b_{c,d} \) is the benefit value. After establishing the mathematical model, we can use intelligent algorithm to optimize it for obtaining the optimal task execution sequence in IWSNs.
3. QES-FLA for Maximizing Sensor Task Allocation Benefit in IWSNs
We use QES-FLA to get the maximum efficiency of sensor task allocation in IWSNs. To achieve the purpose, a novel quantum elite shuffled frog leaping algorithm (QES-FLA) is designed. Firstly, we adopt the quantum probability amplitude in quantum computing to increase the algorithm’s global search capability, and uses quantum revolving gate to enhance the diversity of the solution. Secondly, by using the elite strategy, QES-FLA can preserve the optimal individual in each iteration, which accelerate the convergence of the algorithm. Compared with the traditional SFLA, the proposed algorithm has more advantages, which greatly increase the possibility of finding the optimum or close to the optimal solution. QES-FLA achieves the purpose of heuristic search by exchanging information between frogs. The algorithm steps of QES-FLA are as follows.

3.1. Population coding and initial population generation
In IWSNs, the problem of sensor task allocation is to allocate tasks to sensor nodes for maximizing the task execution benefit. Therefore, to use QES-FLA to solve the task allocation problem, we first determine the coding format of the frog population. Since different tasks have different advantage values, decimal coding is suitable for the frog population. Each individual frog is a solution of the task allocation problem in IWSNs, and the frog is represented by a vector and the length of the vector stands for the dimension of the problem. After determining the encoding method of the frog population, we apply a random method to generate the initial population.

3.2. Fitness calculation and frog grouping
QES-FLA solves the task allocation problem by dividing the frog population into several sub-populations. To achieve the frog grouping operation, we obtain the fitness value of each individual according to the objective function, and then arrange the fitness values in descending order. What’s more, it is necessary to ensure the balance of frog quality in each sub-population when allocating frogs. The purpose of the quality balance is to ensure the effectiveness of the search process. For example, suppose there are \( f \) frogs to be divided into \( g \) groups, and the frogs sorted in descending order are \( \{F_f, F_{f-1}, \ldots, F_{f-g}, \ldots, F_2, F_1\} \). Then \( F_f \) should be placed in the first group, \( F_{f-1} \) should be placed in the second group, \( \ldots \), \( F_{f-g} \) should be placed in the \( g_\text{th} \) group, and so on. After grouping operation, we can obtain a frog population with balanced quality.

3.3. Local search and update
In this section, QES-FLA performs a local search in the frog subpopulation for obtaining the local optimal solution of task allocation. Local search is the core operation of traditional SFLA, and the selection of its search strategy greatly affects the algorithm’s solution accuracy, optimization capability and convergence speed. Furthermore, the moving step length is an important factor in QES-FLA. If the moving step is relatively small, the algorithm will have stronger local search ability, but it is more likely to fall into the local optimum; if the moving step is relatively large, the algorithm will have stronger global search ability, but it increases the possibility of missing the optimal solution at the same time. After weighing, we use the random step length strategy in QES-FLA, which effectively reduces the possibility of the local optimum and also ensures good global search capability.

In QES-FLA, the update way of frog individuals is updating only the worst individual in the sub-population. The purpose of this way of updating is to speed up the execution of the algorithm. Individuals in the sub-population can update their positions with better location individuals around them, thereby accelerating the speed of obtaining the optimal solution of the task allocation in IWSNs. In the local search strategy of QES-FLA, the frog with the lowest fitness value starts to move as far as possible to the better position around it. If the fitness value after moving is higher than the original one, the position of the lowest fitness frog can be updated; otherwise, the move is carried out to the optimal frog in the entire population. If the position after the move is better than the previous position, the individual position is updated, otherwise a random step length is generated for the update operation.
3.4. Quantum operator
The QES-FLA combines the quantum operator, which is a probabilistic search method based on quantum computing. Compared with the traditional SFLA, quantum operator is able to effectively enhance the global search capability and the convergence speed of QES-FLA. QES-FLA is a novel intelligent algorithm, which mainly uses concepts of qubits and quantum superposition states to improve the global search and optimization ability. In QES-FLA, every frog can be converted into binary code, thereby being represented by a set of qubit probability amplitudes. Subsequently, every frog has the ability to search the solution space in parallel, which effectively increases the search efficiency. In QES-FLA, each individual can update the optimal solution through the quantum revolving gate during the evolution process, thus realizing the quantum search mechanism in the iterative process.

3.5. Elite Strategy
The elite strategy of QES-FLA is the establishment of elite population, which purpose is to retain the most adaptive individuals of the previous generation in the population, and then use the elite population to replace the least adaptive individuals in the next generation. Due to the optimal individual may be destroyed by other operations, the elite operator can retain the optimal one to ensure the performance of the algorithm.

The execution of QES-FLA terminates when the specified number of iterations is reached. Otherwise, the grouping and local search operation execute repeatedly until the maximum number of iterations. By updating the quantum probability amplitude and retaining elite individuals in each iteration, the algorithm can obtain the optimal or close to optimal solution of the sensor task allocation problem.

4. Simulation and Results
In this part, we compare the proposed algorithm with SA and PSO for task allocation in IWSNs. To validate the effectiveness of the QES-FLA, we perform simulations. Our experimental environment is an AMD R7 4800H machine with 32 GB RAM and the software is MATLAB 2018b. Furthermore, the objective function (4) is applied to evaluate the task allocation efficiency of sensor nodes in IWSNs. In the experimental situation, the advantage value of all tasks is measured in advance.

To demonstrate the effectiveness of the proposed algorithm, SA and PSO are compared with the QES-FLA. The termination iteration of the three algorithms is 100 iterations, and the algorithm parameters of QES-FLA, SA and PSO are as follows. The size of the population is 50. In QES-FLA, the frog population is divided into 5 groups, each group has 10 frogs. In SA, the initial temperature is 200 and the annealing rate is 0.95. In PSO, the individual learning factor and social learning factor are both 2.

According to fig. 1 and fig. 2, the task allocation benefit values of QES-FLA, SA and PSO are displayed. The parameter settings of the task allocation in the two figures are 20 sensors, 30 tasks and 50 sensors, 80 tasks respectively. To facilitate data processing, we only save the optimal solution during each iteration for each method. All results are averaged after 50 executions. In fig. 1 and fig. 2, we can see that QES-FLA has higher task allocation benefit than SA and PSO, which demonstrates the performance advantage of QES-FLA. In addition, the QES-FLA approach reaches a task allocation benefit value of 12.02 with 20 sensors, 30 tasks, and achieves a benefit value of 34.02 with 50 sensors, 80 tasks. However, SA and PSO cannot obtain the optimal solution, and the task allocation benefit values obtained by SA and PSO are 9.43, 27.11 and 9.09, 26.66, respectively. At the beginning, the task allocation benefit of the three algorithms shows an increasing trend, but after 20 iterations, SA and PSO fall into premature convergence and cannot get the optimal task allocation benefit value.

The convergence performance of the three algorithms is also shown in fig. 1 and fig. 2. Obviously, QES-FLA has the fastest convergence speed among the three algorithms, SA follows it and the PSO has the poorest convergence performance. At the same time, SA and PSO are easy to fall into local optimum, but QES-FLA does not. QES-FLA can stably obtain a group of optimal task allocation sequences for maximizing network efficiency in IWSNs.
Clearly, from the fig. 3 and fig. 4, QES-FLA performs better on obtaining higher task allocation benefit. We can see from the fig.3 that the maximum value of QES-FLA is 16.38 with 25 sensors and 40 tasks, in the same case, the optimal values of SA and PSO are 12.85 and 12.52 respectively. In fig. 4, after 100 iterations, QES-FLA has obtained the optimal task allocation benefit value of 25.69, in contrast, the best values of SA and PSO are 20.43 and 19.72 respectively. Therefore, the proposed QES-FLA method is effective in solving the task allocation problem in IWSNs.

5. Conclusion
In this paper, we establish the mathematical model for the sensor task allocation problem in IWSNs, and design a quantum elite shuffled frog leaping algorithm (QES-FLA) for optimizing the problem. The proposed algorithm can obtain a set of optimal task allocation sequences, thereby effectively improving industrial production efficiency. To verify the effectiveness of the QES-FLA, we compare the algorithm with SA and PSO. The simulation results show that QES-FLA's task allocation benefit is higher than the other two algorithms, which means that QES-FLA is more suitable for solving sensor task allocation problems in the IWSNs.
Acknowledgments
This paper was funded by the Corps innovative talents plan, grant number 2020CB001, project of Youth and middleaged Scientific and Technological In-novation Leading Talents Program of the Corps, grant number 2018CB006, the China Postdoctoral Science Foundation, grant number 220531, Funding Project for High Level Talents Research in Shihezi University, grant number RCZK2018C38, Project of Shihezi University, grant number ZZZC201915B. The corresponding author is Jie Zhou.

References
[1] G. Kunzel, L. S. Indrusiak, and C. E. Pereira, “Latency and Lifetime Enhancements in Industrial Wireless Sensor Networks: A Q-Learning Approach for Graph Routing,” Ieee Transactions on Industrial Informatics, vol. 16, no. 8, pp. 5617-5625, Aug, 2020.

[2] H. R. Faragardi, M. Vahabi, H. Fotouhi et al., “An efficient placement of sinks and SDN controller nodes for optimizing the design cost of industrial IoT systems,” Software-Practice & Experience, vol. 48, no. 10, pp. 1893-1919, Oct, 2018.

[3] L. Sun, L. T. Wan, K. H. Liu et al., “Cooperative-Evolution-Based WPT Resource Allocation for Large-Scale Cognitive Industrial IoT,” Ieee Transactions on Industrial Informatics, vol. 16, no. 8, pp. 5401-5411, Aug, 2020.

[4] Z. C. Zhao, R. Zhao, J. J. Xia et al., “A Novel Framework of Three-Hierarchical Offloading Optimization for MEC in Industrial IoT Networks,” Ieee Transactions on Industrial Informatics, vol. 16, no. 8, pp. 5424-5434, Aug, 2020.

[5] H. Sami, A. Mourad, and W. El-Hajj, “Vehicular-OBUs-As-On-Demand-Fogs: Resource and Context Aware Deployment of Containerized Micro-Services,” Ieee-Acm Transactions on Networking, vol. 28, no. 2, pp. 778-790, Apr, 2020.

[6] H. Wang, S. Tan, Y. J. Zhu et al., “Deterministic Scheduling With Optimization of Average Transmission Delays in Industrial Wireless Sensor Networks,” Ieee Access, vol. 8, pp. 18852-18862, 2020.

[7] Z. C. Hong, W. H. Chen, H. W. Huang et al., “Multi-Hop Cooperative Computation Offloading for Industrial IoT-Edge-Cloud Computing Environments,” Ieee Transactions on Parallel and Distributed Systems, vol. 30, no. 12, pp. 2759-2774, Dec, 2019.

[8] G. Javvaji, and S. K. Udgata, “Soft computing approach for multi-objective task allocation problem in wireless sensor network,” Evolutionary Intelligence, 2020.

[9] M. Tang, Y. Xin, and Y. Qiao, “Multi-objective Resource Allocation Algorithm for Wireless Sensor Network Based on Improved Simulated Annealing,” Ad Hoc & Sensor Wireless Networks, vol. 47, no. 1-4, pp. 157-173, 2020, 2020.

[10] X. Hao, N. Yao, J. Wang et al., “Distributed resource allocation optimisation algorithm based on particle swarm optimisation in wireless sensor network,” Iet Communications, vol. 14, no. 17, pp. 2990-2999, Oct 27, 2020.