GA-based Charger Deployment Algorithm in Indoor Wireless Rechargeable Sensor Networks

Zekun Fang[1], Wei-Che Chien[2], Cong Zhang[3], Nghiem Thuy Hang[4], Wei-Ming Chen[1]*

[1] Department of Information Management, National Dong Hwa University, Taiwan
[2] Department of Computer Science and Information Engineering, National Dong Hwa University, Taiwan
[3] School of Electrical and Electronic Engineering, Wuhan Polytechnic University, China
[4] Department of Chinese Studies, Vietnam National University, Vietnam
zekun.fang@gmail.com, wcc@gms.ndhu.edu.tw, hb_wh_zc@163.com,
nghiemhangvnu@gmail.com, wmchen88@gms.ndhu.edu.tw

Abstract

The advancement of Internet of Things technology has made continuous environmental monitoring a crucial requirement for various applications. To address the issue of the network life cycle, Wireless Rechargeable Sensor Networks (WRSNs) have emerged as a promising solution. This research is focused on WRSN applications in indoor settings such as the Industrial Internet of Things and indoor greenhouses. In such scenarios, rechargeable wireless sensing devices can gather the required information, reducing equipment costs and eliminating the inconvenience of wired sensors. This study proposes the utilization of a genetic algorithm to optimize the deployment of chargers in indoor environments. Compared to greedy algorithms, this approach can determine the best solution for charger deployment and minimize deployment expenses.

Keywords: Wireless rechargeable sensor network (WRSN), Wireless sensor network (WSN), Power consumption, Network planning

1 Introduction

Wireless sensor networks (WSNs) [1-3] have become increasingly prevalent in modern life as people seek to obtain information about a variety of subjects using Internet of Things (IoT) technology. For instance, individuals may want to monitor the health of elderly family members and improve their quality of life. Various sensors can be utilized to gather data such as heart rate, blood pressure, and sleep quality, enabling children to respond to any issues promptly. In other cases, the military may use WSN to collect useful data to ensure the accuracy of commands and prevent the unnecessary sacrifice of soldiers during warfare. Additionally, WSN can be utilized to investigate dangerous environments such as volcanoes and underwater locations that are inaccessible to humans. Sensors have proven to be an effective technology for sensing and monitoring conditions in such harsh environments [4]. It is clear that WSN technology is gradually impacting our daily lives.

Despite its advantages, WSN technology still faces some inherent limitations. WSNs are comprised of wireless sensors and relay nodes that collect and transfer data. However, this process requires power, and the energy of the sensor nodes is limited by their battery capacity. If these sensors are situated in harsh environments, it may not be feasible to replace the battery immediately. As a result, the network can become paralyzed if the relay node runs out of energy. To address this issue, researchers have proposed various solutions to improve the network lifetime [5-8]. Some scholars suggest that all sensor nodes should not operate simultaneously to avoid unnecessary power waste. Instead, proper scheduling of sensor working time can facilitate efficient energy utilization. However, the longevity of WSNs is still determined by the upper limit of the battery's capacity.

To address these issues, researchers have proposed the wireless rechargeable sensor network (WRSN) [9-11], which leverages advancements in wireless power transfer technology. WRSNs consist of chargers, sensor nodes, and sink nodes, with chargers serving as the primary power source. Different wireless power transfer technologies are suitable for various environments, enabling users to select the appropriate charging method based on their needs.

Wireless charging technologies can be classified into two categories based on their suitability for different environments. The first category involves converting renewable energy into alternating current for use by equipment, but it is limited to specific environments. In such cases, sensor nodes may run out of energy when renewable sources are unavailable. The second category comprises wireless power transfer technologies such as magnetic induction, magnetic resonance, laser light, and microwave conversion. Among these technologies, microwave conversion is ideal for long-distance transmission and is well-suited for use in WRSNs.

WRSN can be roughly divided into two types: indoor environment and outdoor environment. The deployment strategy of chargers needs to consider various impacts from those different environments. Most studies focus on outdoor scenarios and little research on indoor scenarios.

Wireless sensor networks have proven to be highly beneficial in indoor settings [12-13], such as in factories where sensors can be used to improve production quality.

*Corresponding Author: Wei-Ming Chen; E-mail: wmchen88@gms.ndhu.edu.tw
DOI: 10.53106/160792642023032402025

Consequently, this study concentrates on optimizing charger deployment in indoor environments, a challenging task that depends on several factors, including sensor placement, RF interference, and charging efficiency. Achieving the optimal solution requires balancing these metrics while considering trade-offs between them.

In previous work, we have proposed the Moveable-Charger-Based Algorithm (MCBA) [14] to deploy chargers. However, MCBA has some defects that it is easy to fall into local optimum because MCBA is a greedy-based algorithm. In order to solve this problem and reduce deployment cost, we try to use the meta-heuristic algorithm to design a charger deployment algorithm.

This paper is structured as follows: Section II provides an overview of related work on charger deployment. Section III formulates and describes the proposed method for addressing the charger deployment problem. Section IV presents and analyzes the simulation results. Finally, Section V offers concluding remarks on the paper and discusses future work.

2 Background and Related Works

To clearly present our thesis, we will introduce the backgrounds of WRSN, previous works and some metaheuristic algorithm as follows.

2.1 Wireless Rechargeable Sensor Network

Wireless charging technologies can be classified into two categories based on their environment. The first type involves the conversion of renewable energy sources, such as wind and solar power, into alternating current to power equipment. However, this method is subject to weather conditions and may not be reliable at all times. The second type comprises wireless power transfer technologies, which include Magnetic Induction, Magnetic Resonance, Laser light, and Micro-wave conversion.

- Magnetic Induction

Magnetic induction is based on the principle that an electric current produces a magnetic field, which can induce a current in a receiver when there is a change in the magnetic field, according to Faraday's law. The main advantage of magnetic induction is its ease of manufacturing. However, it has a limitation in that the distance between the charger and receiver cannot exceed 5mm, and the power consumption increases as the distance increases. Magnetic induction is commonly used in applications such as electric toothbrushes, wireless car charging, and more [15].

- Magnetic Resonance

The addition of capacitors, inductors, and other electronic components to the circuit can cause the detuning of the resonant circuit. If the device vibrates at the same frequency as the charger, it will generate current. The advantage of magnetic resonance is that it allows for long-distance power transmission, with a maximum distance of up to 3 meters. However, it can be difficult to maintain the same vibration frequency over a long period of time. Wireless phone charging is a common application that uses magnetic resonance. [16].

- Laser light sensor

The principle behind laser light sensor charging is similar to that of solar energy generation, where the equipment receives power through the absorption of laser light. However, due to the high power output of laser light, it can pose a risk to human safety and must be used in an obstacle-free environment. Therefore, this charging technology is not commonly used in daily human life. Nevertheless, laser sensors have the advantage of a long transmission distance and excellent charging efficiency. [17].

- Micro-wave conversion

Radio frequency (RF) is a form of energy that can transmit both power and information. Microwave conversion, on the other hand, involves collecting RF energy and converting it into current. There are two types of microwave conversion: directional and omnidirectional antennas. The former has a concentrated power and longer charging distance, but a smaller charging area, while the latter has a fully charged area. Each type of antenna has its own suitable environment. Microwave conversion has the lowest charging efficiency among the four wireless power transfer technologies. Nevertheless, it is still useful because of its longer charging distance and smaller environmental impact compared to other methods. [18].

For the indoor scenarios, RF charging is a promising technology in WRSN. There is some research that used RF wireless power transfer of the directional antenna to provide energy to sensor nodes. In [19], the authors proposed two deployment algorithms, including the greedy heuristic node-based NB-GCS and point-pair-based PB-GCS algorithm deployment methods. In [20], the authors measured received energy of directional antenna angle form 0 to 180°. Due to the limited charging range of directional chargers, it is easy to increase deployment costs. Therefore, in [14], the authors proposed a concept of a charger with a motor to expand the charging area and proposed an MCBA algorithm to deploy chargers.

Although MCBC can find good suitable charging positions, it still has some disadvantages. For example, since MCBA is a greedy-based algorithm, it is easy to fall into local optimum, which increases unnecessary deployment costs. To solve this problem, we use metaheuristic algorithms [21] to deploy chargers because each metaheuristic algorithms have own mechanism to avoid fall into local optimum quickly.

3 Problem Definition

The WRSN scenario can be classified into indoor and outdoor scenarios, with each environment influencing problem definition and solution code. For the purposes of this paper, our focus is on the deployment problem specifically within indoor scenarios.

3.1 Network Model

A wireless rechargeable sensor network model is given as follow. $CC = \{ c_1, c_2, ..., c_m \}$ is set of candidate chargers, $SN = \{ sn_1, sn_2, ..., sn_n \}$ is set of sensor nodes, and $FP = \{ fp_1, fp_2, ..., fp_k \}$ is set of the final position of deployed chargers.

Sensor nodes will be deployed randomly in the 3-dimension space. Each sensor node can receive power from chargers. To reduce the interference of obstacles, chargers will be deployed on the ceiling. The chargers will produce and emit radio waves. Each charger has own Effective Charging Distance (ECD) that sensor can get better-charging efficiency when the distance from sensor nodes to chargers is closer. Assuming that the height of the indoor scenario is less than ECD, we can ensure effective charging for each sensor. In this paper, we use MCBA [14] to find deployment locations of candidate chargers and adopt the concept of a charger with a motor to expand the charging area.

3.2 Wireless Charging Model

The variability in power consumption among sensor nodes, owing to their distinct sensing functions and power requirements, represents a crucial deployment consideration. Consequently, the received power of each sensor are define:

$$P_{i,j}^{sn}\left(d_{i,j}\right)=\frac{G_c G_s \eta}{L_p}\left(\frac{\lambda}{4\pi\left(d_{i,j}+\beta\right)}\right)^2 P_{i,j}^{C}. \tag{1}$$

Where $P_{i,j}^{sn}\left(d\right)$ represent that j^{th} sensor received power from i^{th} charger. $P_{i,j}^{C}$ represents that transferred power from j^{th} charger to i^{th} sensor. G_c is antenna gains of chargers. G_s represents the antenna gains of sensor nodes. η means a value of rectifier efficiency, L_p is polarization loss, λ is RF wavelength, β indicate an adjustable parameter in indoor environment. To ensure that each sensor can be charged, the first step is to find the power required by the most power-hungry sensors. If the provided power can meet the requirements of the most power-hungry sensor, all of the sensors can receive sufficient power in this scenario. In view of this, the ECD is defined in Eq. (2).

$$R=\frac{\lambda}{4\pi\sqrt{\left(\dfrac{PC_{Max}L_p}{hG_cG_s\eta P_{i,j}^{S}\left(d_{i,j}\right)}\right)}}-\beta. \tag{2}$$

Where ER is ECD, PC_{MAX} is the maximum power consumption of all sensors. h is the number of chargers required for the most power-hungry sensors. We assume that $P_{i,j}^{sn}\left(d\right)=PC_{Max}$, the most power-hungry sensor will run out the power which received from chargers. In other words, all sensor nodes will receive sufficient power when the distance from the sensor to the charger is between ER. According to this assumption, ER is also equal to $d_{i,j}$. Eq. (2) can be deduced by Eq. (1). We assume that all of the chargers will provide the same power to have better fairness. The charging efficiency is better when effective charging distance is less than R and vice versa.

3.3 Linear Programing Model

The main goal of this paper is to reduce deployment cost. For better readability, we define a linear programming model for this problem as follows:

$$\begin{aligned}
&\textit{Minimize } F\\
&\quad s.t.\\
&\sum_{j=1}^{m} P_{i,j}^{ss}\left(d\right)\geq PW_i\ ,\\
&\mathrm{P}_{i,j}^{C} > P_{i,j}^{ss}\,,\\
&d_{i,j}\quad \mathrm{ER}\,,\\
&0^\circ \leq \theta \leq 180^\circ,\\
&0^\circ \leq \theta' \leq 180^\circ,\\
&SO \geq n\,.
\end{aligned} \tag{3}$$

The main goal of this thesis is that minimize the number of chargers F_i and make sure that each sensor can continue to work; it is given by:

$$F=\frac{SC}{SO},$$

SC represents the total number of covered sensors. Note that each sensor node may be covered more than once. O is a number of covered overlaps for all sensors.

A large number of chargers will lead to more deployment cost. Conversely, fewer chargers will cause the power of the sensor node to be exhausted. Therefore, the most important thing is to balance the two metrics. To make this research closer to reality, we define some constraints. The first restriction is to make sure that sensor nodes can continue work. Therefore, sensor nodes collect totally power must larger or equal than power consumption. According to the energy conservation law, the power provided by the charger needs to be greater than the received power of the sensor node because of transmission loss, which is shown in the second restriction. To guarantee sensor nodes will be charged exactly, the third restriction is to restrict effective charging distance. The fourth limit condition limits the horizontal movement angle of the motor (θ), so the value is defined between 0 ° and 180 °. Fifth restriction limits the rotation angle of motor. θ' is the rotation angle of motor, between 0° to 360°. Figure 1 shows θ and θ'. The final restriction is to ensure any sensor node will be covered at least one charger.

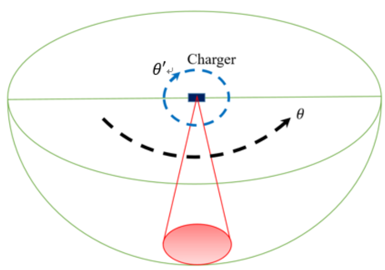

Figure 1. Rotation angle of motor

To evaluate the performance of our proposed method, we prove the lower bound of the number of chargers in this study.

Proof: the lower bound of the number of chargers

In order to determine that the metaheuristics can run successfully, the length of the solution must be defined firstly. Since the candidate position is found by the gravity center of the triangle, the maximal number of candidate positions can be estimated as long as the number of triangles generated by the sensors is found. The equation for triangle finding is shown as follows:

$$\frac{Ns(Ns-1)(Ns-2)}{6}. \quad (3)$$

However, this is an upper bound of the number of candidate positions. Because each sensor has a limited transmission radius, this situation only presents a high density scenario where all the sensors can cover each other. Therefore, the transmission range of each sensor must be considered, as shown in the following restriction:

$$R_i + R_j > \overline{C_i C_j}, \quad (4)$$

where C represents the center of the circle and R is the radius. It guarantees that an overlapping area exists between two such circles so that some unnecessary cases will be avoided, which includes sensors too far away. In other words, we only find the triangles in the neighborhood of each sensor. According to the above equation, the set of sensors' neighborhood $Nb = \{Nb_1, Nb_2, \ldots, Nb_{Ns}\}$ can be obtained; thus, we can derive the new number of triangles. Two cases should be determined first. Because we know that the number of sensors may not be divisible, hence in the first case, the number of the sensors in the neighborhood is equal to 3 (including itself) that is noted as n_{three}. It also represents the number of centers of the circle than can be derived by using the following:

$$n = n_{three} + n_{lessthree}, \quad (5)$$

Since the main goal of this paper is to find maximal coverage but without minimal chargers, we must prove that the low bound is there. The low bound is a way to evaluate the availability of the proposed method. The proof is shown as follows:

$$m \times n \geq \pi \sum_{i=1}^{k} r_i^2 - \alpha, \quad m, n \in N. \quad (6)$$

Where m and n are the length and width of the space, $ð\sum_{i=1}^{k} r_i^2 - \alpha$ is total covered area by charger.

$$\sum_{i=1}^{N_1} a_1 + \sum_{i=1}^{N_2} a_2 + \ldots + \sum_{i=1}^{N_m} a_m \geq N, \quad (7)$$

$\sum_{i=1}^{N_m} a_m$ represents charger N_m covered number of a_m sensor nodes. N is total number of sensor nodes. A = { a_1, a_2, …, a_m } is a decreasing series, the max(A) = a_1.

Goal: $\exists$!k : inf (S)

Proof:

$\because$ (1)(2) $\therefore N_1 + N_2 + \ldots + N_m \geq k$ if $\lim_{m\to\infty}(a) = 0$;

Assume $\exists L < k,\ s\ t\ L < \sum_{i=1}^{m} N_i$;

$\because\ \exists\ a_0 > a_1\ s.t.\ \max(A) \neq a_1 >< \therefore \exists!k : \inf(S)$

4 Proposed Mechanism

This paper introduces a GA-based Charger Deployment Algorithm (GACD) aimed at minimizing the deployment cost. GACD comprises three steps, with the chromosome representing the solution and the gene representing a candidate position. The first step involves selection, whereby a superior solution is identified based on the fitness function (F) to enhance convergence. The second step is crossover, where chromosomes exchange genes, resulting in better solutions as superior chromosomes are selected in the selection step. The final step, mutation, offers an opportunity for genes to alter their status in each chromosome, thus enhancing the solution's ability to avoid local optima.

Figure 2 shows the coding diagram of GACD. First step is to create L chromosomes because it needs different chromosomes for evolution, so genes of chromosome have different status. In second step, we need to calculate F. Third step is selection which can choose a better solution by F. Fourth step is crossover. Fifth step is mutation. All of the above steps will repeat until the termination criterion is not met.

Table 1 shows the pseudo-code of the GACD algorithm. First step is to randomly create the initial chromosomes which length is N_c that is shown in line 1 of Table 1. Note that each status of gene will be created randomly that making sure the biological diversity. Then, each chromosome will calculate the F that is shown in line 3 of Table 1. Next step is selection that randomly choosing two chromosomes to compare them with F then save the better one that is shown in line 4 of Table 1. Next step is crossover that randomly choosing two chromosomes then exchanging the gene randomly that is shown in line 5 of Table 1. Next step is mutation. randomly choosing genes to exchange their status. For example, a candidate charger will change its status from "to be deployed" to "not to be deployed" that is shown in line 6 of Table 1. Finally, repeating this process until termination criterion is met so that the best chromosome will be found.

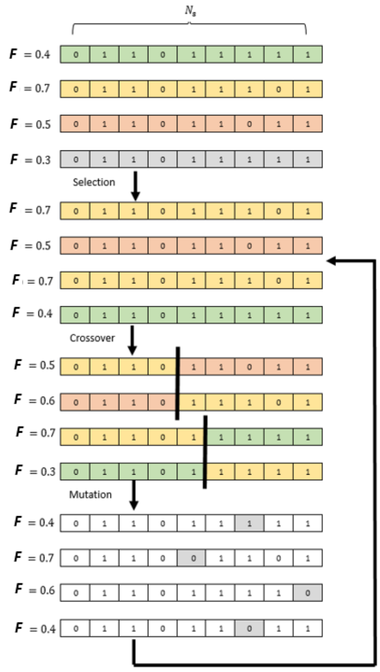

Figure 2. The coding diagram of GACD

Table 1. GA-based Charger Deployment algorithm (GACD)

GA-based Charger Deployment algorithm (GACD)
1. Randomly create the initial chromosome which length is N_c
2. Repeat
3. Calculate the F n for each chromosome
4. Selection
5. Crossover
6. Mutation
7. Until the termination criterion is met
8. Select the best solution as FP

5 Simulation Results

We adopt Matlab (Version 7.11, R201b) as experiment platform. The scenario of our thesis is in 30 × 25 × 3 indoor environment. Number of sensor nodes set as 50 to 400 and there are randomly deployed. The effectual charger distance is 5 m. The details of simulation parameters are shown in Table 2. Figure 3 shows the charger deployment results for 400 sensor nodes. The blue points are the sensor nodes, and the green circles are the area covered by the chargers.

Table 2. Simulation parameters

Parameters	Value
Size of the venue	$30 \times 25 \times 3\ m^3$
The number of sensor nodes	50-400
Effectual charger distance	5m

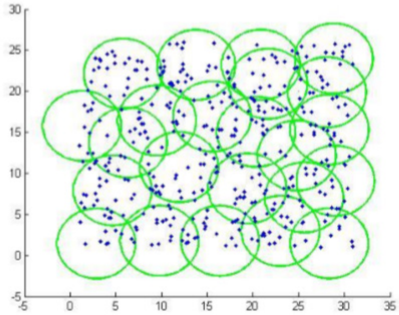

Figure 3. Charger deployment results for 400 sensor nodes

Figure 4 shows the convergence curve of GACD. GACD will converge at 30-40 iterations. The green line is lower bound of number of chargers. The lower bound value is based on the result that the charging areas do not overlap. Although the number of chargers used by GACD is slightly higher than the Lower bound, it is understandable because the sensor nodes are randomly distributed, so the charging ranges will overlap at a certain density.

We compare the number of chargers deployed by MCBA and GABC when the number of sensing nodes increases from 50 to 400, as shown in Figure 5. As the number of sensing nodes increases, the number of chargers used by MCBA is significantly higher than GABC. The reason is that the deployment method adopted by MCBA is based on the greedy method. In the process of finding solutions, it will preferentially find the location where can cover the largest number of sensing nodes. It will cause some edge nodes to require more chargers for coverage. In other words, it is easy to fall into the optimum solution when number of sensing nodes increases. For GACD, when the number of sensing nodes is greater than 300, the number of deployed chargers tends to be stable. The reason is that in the same space, the increase in sensor density allows the charger to cover more sensing nodes. For GACD, about 24 chargers can serve almost sensor nodes. Of course, this will change due to the different distribution of sensor nodes.

Figure 6 shows the comparison of computer processing time and number of sensing nodes Although the proposed GACD can reduce the probability of falling into local optimum, it also takes more calculation time. An increase in the number of sensing nodes will inevitably lead to an increase in the computer processing time of the algorithm However, GACD requires a lot of computer processing time compared with MCBA. The reason is that the complexity of GACD results in a large amount of computer processing time. However, the deployment of the charger is a prior work, so it is acceptable to increase the time cost in exchange for the deployment cost.

The results show that the metaheuristic-based method algorithm can discover more solution space than the greedy-based algorithm. Compared with the single-solution algorithm, the multi-solution algorithm can provide better quality due to the designed strategy being different and the concept. However, although the GACD has good performance, they still need more computation time for calculating the fitness function within any solution. Therefore, GACD is still suitable for a one-time operating scenario. In addition, since the original GA has more diversified searching capabilities, it may be suitable for the multiple categories sensors scenario. The detailed comparison as shown in Table 3.

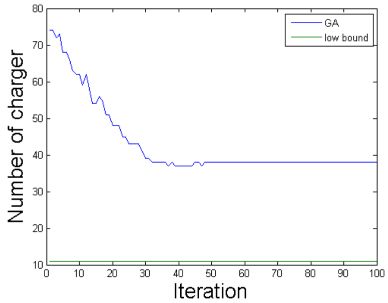

Figure 4. The convergence curve of GACD

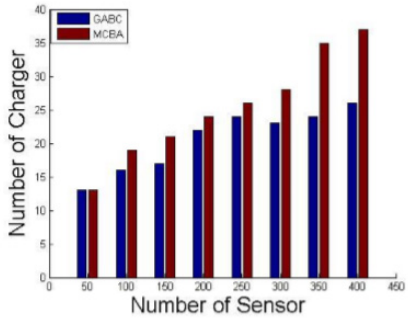

Figure 5. Comparison of the number of sensor nodes and the chargers

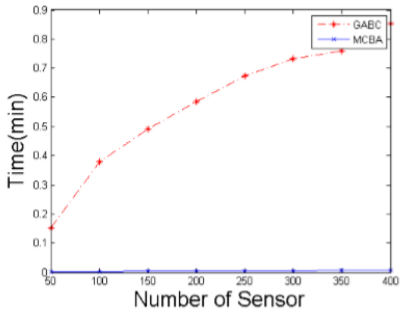

Figure 6. Comparison of computer processing time and number of sensing nodes

Table 3. Comparison of GACD and MCBA

Name	GACD	MCBA
Category	Multi-solution	Single-solution
Strategy	Metaheuristic-based method	Greedy-based method
Status of coverage (iteration)	Part of sensors will be covered	Part of sensors will be covered
Concept	Deciding deployment status randomly	Deciding deployment status by greedy rules

6 Conclusion and Future Work

WSNs often face the challenge of limited lifespan, making WRSN an important technology. Proper charging planning can achieve energy-saving and sustainable development of WSN. This study focuses on indoor charger deployment, utilizing chargers with motors to expand the charging area and reduce obstacle interference. To address the local optimum problem with greedy algorithms, we propose the GACD algorithm, which removes bad solutions through selection, improves solutions through crossover and avoids local optimum with mutation. Simulation results demonstrate that the GACD algorithm effectively reduces deployment costs. Future work will consider radio wave interference and charger scheduling to establish a complete indoor charging mechanism.

Acknowledgment

This work was supported in part by the National Science and Technology Council of Science and Technology of Taiwan, R.O.C., under Contracts 111-2221-E-259 -008 - as well as was partially supported by Vietnam National University, Hanoi (VNU), project number QG 20-35.

References

[1] H. Landaluce, L. Arjona, A. Perallos, F. Falcone, I. Angulo, F. Muralter, A review of IoT sensing applications and challenges using RFID and wireless sensor networks, *Sensors*, Vol. 20, No. 9, Article No. 2495, May, 2020.

[2] M. Majid, S. Habib, A. R. Javed, M. Rizwan, G. Srivastava, T. R. Gadekallu, J. C. W. Lin, Applications of wireless sensor networks and internet of things frameworks in the industry revolution 4.0: A systematic literature review, *Sensors*, Vol. 22, No. 6, Article No. 2087, March, 2022.

[3] W. C. Chien, C. F. Lai, H. H. Cho, H. C. Chao, A SDN-SFC-based service-oriented load balancing for the IoT applications, *Journal of Network and Computer Applications*, Vol. 114, pp. 88-97, July, 2018.

[4] G. Han, J. Jiang, L. Shu, J. Niu, H. C. Chao, Management and applications of trust in Wireless Sensor Networks: A survey, *Journal of Computer and System Sciences*, Vol. 80, No. 3, pp. 602-617, May, 2014.

[5] N. A. Prasad, H. V. Chaitra, G. Manjula, M. Shabaz, A. B. Martinez-Valencia, K. B. Vikhyath, S. Verma, J. L. Arias-Gonzáles, Delay optimization and energy balancing algorithm for improving network lifetime in fixed wireless sensor networks, *Physical Communication*, Vol. 58, Article No. 102038, June, 2023.

[6] K. Jain, P. S. Mehra, A. K. Dwivedi, A. Agarwal, SCADA: scalable cluster-based data aggregation technique for improving network lifetime of wireless sensor networks, *The Journal of Supercomputing*, Vol.

78, No. 11, pp. 13624-13652, July, 2022.

[7] W. Ouyang, C.-W. Yu, C.-C. Tien, C.-W. Hao, T.-H. Peng, Wireless Charging Scheduling Algorithms in Wireless Sensor Networks, *Journal of Internet Technology*, Vol. 13, No. 2, pp. 293-305, March, 2012.

[8] D. Rajesh, T. Jaya, RETRACTED ARTICLE: Enhancement of network lifetime by fuzzy based secure CH clustered routing protocol for mobile wireless sensor network, *Journal of Ambient Intelligence and Humanized Computing*, Vol. 13, No. 5, pp. 2795-2805, May, 2022.

[9] L. V. Quan, P. Le Nguyen, T. H. Nguyen, K. Nguyen, Q-learning-based, Optimized On-demand Charging Algorithm in WRSN, *2020 IEEE 19th International Symposium on Network Computing and Applications (NCA)*, Cambridge, MA, USA, 2020, pp. 1-9.

[10] M. Zhao, J. Li, Y. Yang, Joint Mobile Energy Replenishment and Data Gathering in Wireless Rechargeable Sensor Networks, *2011 23rd International Teletraffic Congress (ITC)*, San Francisco, CA, USA, 2011, pp. 238-245.

[11] C. Hu , Y. Wang, Minimizing Energy Consumption of the Mobile Charger in a Wireless Rechargeable Sensor Network, *Journal of Internet Technology*, Vol. 16, No. 6, pp. 1111-1119, November, 2015.

[12] J.-H. Liao, J.-R. Jiang, Wireless Charger Deployment Optimization for Wireless Rechargeable Sensor Networks, *The 7th International Conference on Ubi-Media Computing (UMEDIA 2014)*, Ulaanbaatar, Mongolia, 2014, pp. 160-164.

[13] J.-H. Liao, C.-M. Hong, J.-R. Jiang, An Adaptive Algorithm for Charger Deployment Optimization in Wireless Rechargeable Sensor Networks, in: W. C. C. Chu, H. C. Chao, S. J. H. Yang (Eds.), *Intelligent Systems and Applications*, IOS Press, 2015, pp. 2080-2089.

[14] W.-J. Jian, H.-H. Cho, C.-Y. Chen, H.-C. Chao, T. K. Shih, Movable-charger-based planning scheme in wireless rechargeable sensor networks, *2015 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, Hong Kong, China, 2015, pp. 144-148.

[15] O. H. Stielau, G. A. Covic, Design of loosely coupled inductive power transfer systems, *PowerCon 2000. 2000 International Conference on Power System Technology*, Perth, WA, Australia, 2000, pp. 85-90.

[16] M. Kiani, M. Ghovanloo, The circuit theory behind coupled-mode magnetic resonance-based wireless power transmission, *IEEE Transactions on Circuits and Systems I: Regular Papers*, Vol. 59, No. 9, pp. 2065-2074, September, 2012.

[17] N. N. Ching, H. Y. Wong, W. J. Li, P. H. Leong, Z. Wen, A laser-micromachined multi-modal resonating power transducer for wireless sensing systems, *Sensors and Actuators A: Physical*, Vol. 97-98, pp. 685-690, April, 2002.

[18] N. Shinohara, Power without wires, *IEEE Microwave Magazine*, Vol. 12, No. 7, pp. S94-S73, December, 2011.

[19] S. He, J.-M. Chen, F. Jiang, D. Y. Yau, G. Xing, Y.-X. Sun, Energy Provisioning in Wireless Rechargeable Sensor Networks, *IEEE transactions on mobile computing*, Vol. 12, No. 10, pp. 1931-1942, October, 2013.

[20] Y. C. Chen, J. R. Jiang, Particle swarm optimization for charger deployment in wireless rechargeable sensor networks, *2016 26th International Telecommunication Networks and Applications Conference (ITNAC)*, Dunedin, New Zealand, 2016, pp. 231-236.

[21] S. Desale, A. Rasool, S. Andhale, P. Rane, Heuristic and meta-heuristic algorithms and their relevance to the real world: a survey, *International Journal of Computer Engineering in Research Trends*, Vol. 2, No. 5, pp. 296-304. May, 2015.

Biographies

Zekun Fang received his B.A degree from Anhui University, China in 2006, his M.Sc degree from University of Bristol, United Kingdom in 2007, and his M. Phil degree from University of Oslo, Norway in 2009. He is currently a PhD student at Department of Business Administration, National Dong Hwa University, Hualien, Taiwan. His research interests include information management system and application in e-commerce, big data and data mining, information system application in digital learning

Wei-Che Chien received his B.S. and M.S degree in Computer Science and Information Engineering from the National ILan University, I-lan, Taiwan in 2014 and 2016, and the Ph.D. degree in the Department of Engineering Science from National Cheng Kung University, Tainan, Taiwan, in 2020. He is currently an Assistant Professor with the Department of Computer Science and Information Engineering, National Dong Hwa University, Hualien, Taiwan. His research interests include wireless rechargeable sensor networks, 5G mobile networks, AIoT, fog computing and cloud computing.

Cong Zhang received the bachelor's degree in automation engineering from the Huazhong University of Science and Technology in 1993, the master's degree in computer application technology from the Wuhan University of Technology in 1999, and the Ph.D. degree in computer application technology from Wuhan University in 2010. He is currently a Professor with the School of Electrical and Electronic Engineering, Wuhan Polytechnic University. His research interests include Multimedia Signal Processing and Network Communication Technology, Artificial Intelligence and Big Data Technology.

Nghiem Thuy Hang received her BA degree in Translation and Interpriting from Hanoi University in 1992, BA degree in Linguistic and Apply Linguistic from University of Social Sciences and Humanities in 1996, MA degree in Linguistics and Apply Linguistics at Beijing Language and Culture University, China in 2012, PhD in Linguistic and Apply Linguistic from Beijing Language and Culture University, China in 2016. She is currently Senior Lecturer at Department of Chinese Studies, USSH, Vietnam National University, Hanoi. Her research interest include Dialects, Corpus Linguistics, Machine Learning, Machine Translating, Natural Language Processing, AIoT

Wei-Ming Chen is currently a professor in the Department of Information Management at National Dong Hwa University. At the same time, he is also the director in University Library and Information Center. He was a professor in the Department of Computer Science and Information Engineering and the Chairman of Computer Science and Information Engineering at National Ilan University. He received his M.E. and Ph.D. degrees in Computer Science and Information Engineering from National Chung Cheng University. His current research interests include image processing, computer networks, multimedia systems, and artificial intelligence.