Beampattern optimization techniques using metaheuristic algorithm for collaborative beamforming: a review

Najla Ilyana Ab Majid, Nik Noordini Nik Abd Malik, Nor Aini Zakaria
School of Electrical Engineering, Faculty of Engineering, Universiti Teknologi Malaysia, Johor Bahru, Malaysia

Article Info

Article history:

Received Sep 21, 2022
Revised Nov 9, 2022
Accepted Jan 11, 2023

Keywords:

Beampattern optimization
Collaborative beamforming
Distributed networks
Metaheuristic algorithms
Wireless sensor networks

ABSTRACT

The fast improvements in wireless technology and embedded systems have sparked a renewed interest in collaborative beamforming (CB) approach used in wireless sensor networks (WSNs). Despite the fact that studies on distributed and CB have been conducted for more than 10 years, CB was previously deemed unworkable because of its extreme complexity and difficult-to-attain criteria. It just got well-known in the last several years when cheaply accessible compact wireless communication electronic sensors with high processing capability emerged. These factors contributed as the motivation for this paper's research overview CB in WSNs. We provide the classifications of the static and mobile WSN which is based on the sensor node optimization technique. This paper reviews the metaheuristic algorithms proposed by previous study for beampattern and energy consumption optimization. Finally, this paper also presents a summary analysis of the previous studies in terms of beampattern characteristic and properties, energy consumption and stability.

Corresponding Author:

Nik Noordini Nik Abd Malik
School of Electrical Engineering, Faculty of Engineering, Universiti Teknologi Malaysia (UTM)
Skudai, 81310 Johor Bahru, Johor, Malaysia
Email: noordini@utm.my

1. INTRODUCTION

In our daily lives, wireless sensor networks (WSNs) are becoming a necessity. These networks of spatially distributed autonomous sensors are used in a variety of applications including smart homes, emergency response, healthcare, entertainment, transportation, the military, and environmental monitoring [1]. Since each sensor in the WSN must be able to simultaneously sense, gather, analyze, and communicate data, achieving power-efficient communication for data transfer is crucial. In collaborative beamforming (CB), independent nodes that are randomly located work together to create a virtual antenna array (VAA) in a WSN as shown in Figure 1. CB is a very recent study area that has just recently attracted the attention of wireless communications researchers. CB is useful for sensors with limited resources and battery life, especially in situations where the network is installed in locations that is challenging to repair or recharge the power source [2], [3]. Collaborative communication in WSN increases the lifetime of sensor nodes. Another advantage of CB is the ability to perform the long-distance transmission where sink node and multi-hop transmission are inappropriate [4].

Compared to conventional antenna array, CB provides a significant gain in the received signal-to-noise ratio (SNR) where an ideal CB with N collaborating nodes produced in N^2 fold gain [5]. CB node needs to perform synchronization individually due to its distributed characteristics. Thus, previous studies focused on beampattern analysis and random array theory while assuming perfect phase synchronization. The beampattern of an antenna is the power distribution surrounding the antenna which is amount of energy focused in a particular direction during transmission or reception. Beampattern characteristics such as beamwidth, main lobe and sidelobe is derived from mathematical model which can be manipulated by the number and spacing of antenna elements, signal wavelength and beamforming coefficient [5]. The concept of manipulating the factors is called beampattern optimization.

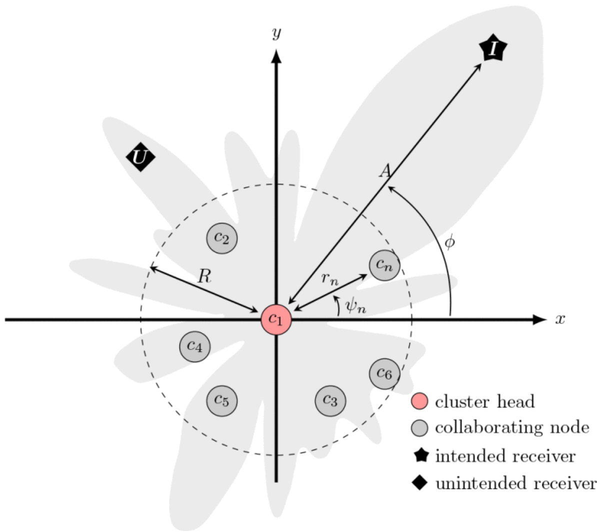

Figure 1. Randomly distributed sensor nodes perform CB through VAA [6]

Optimization is the process of finding the best solution among a set of possible solutions which is applied to maximize profits or minimize cost [7]. There are several optimization methods to solve different kinds of optimization problems. Optimization methods and algorithms are divided into deterministic algorithms and approximate algorithms [8]. Deterministic algorithms are able to find optimal solution accurately. However, it is insufficient to solve non-deterministic polynomial time hard (NP-hard) optimization problems and the execution time of deterministic algorithms increases exponentially with the dimension of the problems [8]. Compared to deterministic algorithms, approximate algorithms are able to find near optimal solutions in a short time for NP-hard optimization problems [8]. Approximate algorithms are categorized into heuristic algorithms, meta-heuristic algorithms and hyper-heuristic algorithms. Meta-heuristic algorithms are capable of providing exit strategies from local optimal points. It is divided into single-solution and population-based [5]. In single-solution technique, the optimization starts with a random solution and improves it with repetition. The technique is simple and has a low number of evaluation functions but weak in finding optimal local point [8]. In population-based technique, the optimization process starts with a set of random solutions and improves with repetition. The technique has high evaluation functions and is able to share information to other objects [8], but it is important to consider the balancing of exploitation and exploration to ensure the optimal solution. This technique comprises of evolution, physics and particles. These algorithms include particle swarm optimization (PSO) [9], genetic algorithm (GA) [10], backtracking search algorithm (BSA) [11], chicken swarm optimization (CSO) [12], firefly algorithm (FA) [13], and cuckoo search algorithm (CSA) [14].

2. COLLABORATIVE BEAMFORMING PROPERTIES AND ANALYSIS

Beampattern optimization can be achieved by beamforming coefficient perturbation or node perturbation method [5]. Beamforming coefficient perturbation can be done by optimizing one or both amplitude and phase of the signal. Whilst node perturbation can be done by optimizing node selection or node location. Node location involves carefully choosing the optimal site for each antenna and positioning it, whereas node selection works on the basis that the position of the antenna elements in an array are selected [5]. Most commonly, metaheuristic algorithms are employed to solve beampattern optimization problems by employing intensification and diversification to assure convergence to the global optimum [5]. Metaheuristic approaches are more effective in finding a near-optimal solution. When metaheuristic techniques are used to optimize beampattern properties CB, the objective function is iteratively optimized. As a result, in addition to the value optimal beampattern solution, the speed of the algorithm converging to the best solution is regarded as a measure of performance [5].

Beampattern optimization research in CB has its own set of advantages and disadvantages. The most common theme in CB beampattern optimization is nulling schemes. The collaborating nodes are adjusted to produce a null towards an unintended receiver. This is accomplished using node selection method [15], [16] and both perturbation method [17], [18]. Reducing the peak sidelobe level (PSL) of the beam pattern is a common technique for reducing sidelobes. The node perturbation method has been used in recent study to reduce PSL [16], [19]–[25]. Meta-heuristic optimizations are used to attempt to reduce PSL using the coefficient perturbation approach [26]–[28]. There is also a combination of both perturbation methods to reduce PSL [29]–[33]. However, it has recently been found that PSL minimization is better suited to small clusters with a high sensor node density and does not always equate to interference reduction and network capacity improvement [6]. The studies in in Jayaprakasam *et al*. [6] and Macharia *et al*. [34] attempt at maximization of the beampattern directivity in CB to increase the capacity.

There are also several studies have started focusing on the statistical properties of the beampattern in CB, including the three-dB beamwidth of the average beampattern [33] and complementary cumulative distribution function (CCDF) [6], [33]. These statistical properties serve as a performance benchmark and performance reference for later efforts on beampattern optimization and analysis in CB. However, to successfully establish a communication link with the receiver, each collaborating sensor node in the CB does not require to transmit at its maximum transmit power. To reduce overall power consumption and increase network lifetime, one of the research areas for distributed and CB is efficient power allocation. According to the literature, there are no established performance indicators for assessing power and longevity enhancement in CB [5]. But in energy or power optimization literature, the optimization objective is frequently the energy consumption [17], [23]–[25], [29], [30], [33], [35], SNR [35], stability test [33], [35], motion energy [35], total transmission time [25], total performing time [25], communication delay [29], [30] and capacity [6], [33].

3. BEAMPATTERN PROPERTIES OPTIMIZATION TECHNIQUE

It is important to get desirable beampattern characteristics which can improve the transmission performance of CB. Due to randomness of sensor node's location, CB produces beampattern with high sidelobe level (SLL) which cause high interference in communication [36]. Thus, it is important to suppress SLL and increase directivity of beampattern to reduce interference. Node placement and selection method is a way to suppress SLL and increase directivity of beampattern. Besides, each node has different transmit power which needs to be considered in optimization to be more efficient for extending the sensor nodes lifetime. However, different types of WSN will have different methods to optimize the nodes perturbation and coefficient perturbation. WSN consists of static and mobile characteristics. Optimization of static and mobile WSN is performed to achieve one or more objectives which are maximizing directivity or SNR, minimizing PSL or overall sidelobe, minimizing overall and per element power consumption and reducing interference at unintended target. Figure 2 shows the summary of beampattern optimization techniques for static WSN and mobile WSN.

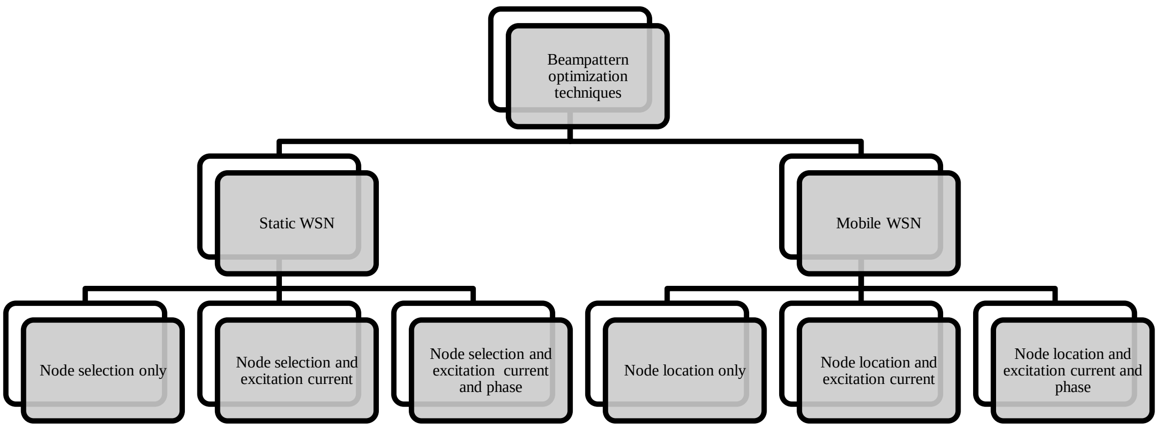

Figure 2. Summary of beampattern optimization techniques of CB

3.1. Static wireless sensor network

Once the sensor nodes are employed, the location of nodes cannot be moved from their current placement. Hence, an optimal number of sensor nodes should be selected from random nodes to form VAA of CB. The optimal number of sensor nodes should produce beampattern with minimal sidelobe to reduce interference as shown in Table 1 (see in appendix). The selected nodes can form a linear antenna array (LAA), circular antenna array (CAA) or random antenna array (RAA) [37]. A CB null steering and linear array (CBNL) based on PSO [15] and inteligence linear sensor node array (ILSA) optimizes by hybrid least sqaure improved PSO (HLPSO) [16] are proposed to select CB nodes in LAA form. Both methods aim to minimize PSL, control first null beam width (FNBW) at desired direction and placing nulls towards unintended receivers. A PSO linear sensor node array (PSO-LSNA) also is proposed to select node to form LAA to minimize PSL [19]. There are also several approaches that propose a node selection method to form CAA using PSO [36] and BSA [38] to optimize maximum PSL and reduce power consumption. Furthermore, a comparative study by [20], proposed greedy deployment algorithm (GDA), metropolis algorithm (MA) and GA to select number of nodes to form LAA and RAA. The algorithms propose are aimed to reduce maximum PSL and computational complexity.

Aside from optimizing node selection, excitation current and phase of RAA also can be optimized without node selection. Jayaprakasam *et al*. [6] used GA to optimize excitation current of collaborative nodes which have no knowledge and feedback from unintended receivers. The study is aimed to reduce overall sidelobe by maximizing directivity of main lobe. A similar technique and objectives are proposed by Macharia *et al*. [34] using gravitational seach algorithm (GSA). Variants of CSO are also proposed to optimized excitation current which are bat-CSO (BCSO) [39] and improved CSO (ICSO) [26]. Both techniques successfully fulfil the objectives to reduce PSL and transmission power consumption during CB. There are other approaches in optimizing excitation current are culled fuzzy adaptive PSO (CFAPSO) [27] and biogeography-based optimization with improved migration and adaptive mutation (BBOIMAM) [28] which aim to reduce maximum PSL. Besides, a non-dominated sorting GA with selective distance (NSGA-SD) is proposed to minimize PSL and maximize directivity of main lobe by optimizing excitation current and phase of random nodes [40]. Maina *et al*. [41] propose FA to optimize the excitation current and phase of RAA which able to reduce PSL and transmission power consumption during CB. However, the node selection technique only will increase SLL and as well as excitation weight without selected optimal node will increase energy consumption of nodes during CB.

Thus, to reduce the energy consumption and reduce SLL of CB, the combination of node selection scheme and excitation weight is crucial. Sun *et al*. [29] proposed node sidelobe control by node selection algorithm (SCNSA) to reduce SLL and energy consumption of nodes. The node selection algorithm in SCNSA calculates the optimal number of array node from 1,000 random nodes to form LAA. CSA is used in SCNSA to optimize the excitation current of selected node. A node selection optimization algorithm (NSOA) is proposed by [30] to select optimal number of nodes to form CAA and optimize excitation current by FA. NSOA able to reduce SLL and energy consumption of nodes. There are also some variants of CSO proposed in optimization scheme to reduce SLL and energy consumption of nodes. Sun *et al*. [31] proposed a sidelobe and energy optimization array node selection (SEOANS) to select nodes to form CAA. Cuckoo search chicken swarm optimization (CSCSO) is used in SEOANS to optimize excitation current of selected nodes. Besides, Sun *et al.* [32] proposed hybrid optimization approach (HOA) to select nodes to form concentric circular antenna array (CCAA) and optimized excitation current by variation particle chicken swarm optimization (VPCSO).

The analysis is extended Liang *et al.* [33] which proposed joint sidelobe suppression approach (JSSA) to reduce SLL and energy consumption of nodes. A hybrid discrete continuous optimization (HDCOP) is proposed by [17] which is a combination of binary model and continuous model to reduce SLL and transmission power. Improved discrete CSA (IDCSA) is proposed in discrete part to select optimal number of nodes, while chaotic hierarchy CSA (CHCSA) is introduced in continuous part to optimize excitation current of selected nodes. Distributed parallel CSA (DPCSA) is proposed to run IDCSA and CHCSA in parallel to achieve better computing efficiency. Other than that, canonical PSO (CPSO) is proposed by [18] to reduce SLL and increase main lobe directivity by investigating the effect of random deployment of disjointed sensors. A node selection scheme based on CPSO is introduced to optimize the node selection of VAA and excitation phase and current.

3.2. Mobile wireless sensor network

WSN also consists of mobile sensor nodes which are attached to people, animals, autonomous vehicles, unmanned vehicles and manned vehicles. MWSN can be deployed in any scenario. MWSN are used in environment monitoring or surveillance. Mobile WSN is also equipped with antenna and limited power resource. Thus, due to the mobility of MWSN, long distance communication between sensor nodes and base station is impossible through multi-hop communication as it can increase motion energy and transmission power as well as communication delay [21]. As a solution, MWSN can form a VAA to perform CB. As compared to static WSN, the location of nodes in MWSN can be manipulated and form VAA. There are several approaches in optimizing the location of MWSN and excitation weight to produce desired beampattern so that can reduce transmission power and motion energy as shown in Table 2. Improved CSA (IPCS) is used to optimize node location of CB nodes [22]. Liu *et al*. [35] proposed a PSO with weed optimization mechanism (PSOWOM) to optimize random location of unmanned aerial vehicle-VAA (UAV-VAA) to jointly increase SNR and reduce motion energy.

Besides, Sun *et al.* [21] proposed a multi-objective optimization framework (MOF) to jointly reduce SLL, increase transmission rate and reduce motion energy by optimizing location and excitation current of MWSN. Improved non-dominated sorting GA (INSGA-II) is introduced in MOF to improve computer efficiency and accuracy. Liang *et al*. [42] proposed a DPCSA to jointly reduce SLL, increase transmission rate and reduce motion energy by optimizing location and excitation current of MWSN. Moreover, a multi-objective optimization problem (MOP) is proposed by [43] to optimize location and excitation current of MWSN. INSGA-II and distributed parallel improved non-dominated sorting GA (DPINSGA-II) are introduced in MOP to improve computing efficiency and accuracy. An improved multi-objective dragonfly algorithm (IMODACH) is proposed by [23] to maximize total secrecy rate for multi-BSs by optimizing location and excitation current weight UAVs.

Furthermore, Wang *et al*. [24] proposed a high data transmission rate MOP (HDTRMOP) to optimize location and excitation current of MWSN to communicate with UAVs as multi-BS. INSGA-III is introduced to solve NP-hard HDTRMOP. Sun *et al.* [25] proposed a time and energy minimization communication MOP (TEMCMOP) to optimize location, flight speed and excitation current of UAVs so that it can reduce total transmission time, total performing time and total energy consumption. The solution dimension of TEMCMOP is reduced to R-TEMCMOP which consists of continuous and discrete solution. Improved multi-objective ant lion optimization (IMOALO) to solve NP-hard of R-TEMCMOP.

Table 2. Summary of beampattern optimization technique for mobile WSN

Papers	Objectives	Perturbation scheme	Metaheuristic algorithm
[21]	PSL minimization, increase transmission rate and reduce motion	Optimize node location and excitation current	INSGA-II
[22]	PSL minimization	Optimize node location	IPCS
[23]	PSL minimization, increase transmission rate and reduce motion by maximizing directivity of main lobe	Optimize node location and excitation current	IMODACH
[24]	PSL minimization, increase transmission rate and reduce motion	Optimize node location and excitation current	INSGA-III
[25]	Minimize total transmission time, total performing time, total energy consumption	Optimize node location and excitation current to get optimize fligt speed	IMOALO
[35]	Increase SNR and reduce motion energy	Optimize node location	PSOWOM
[42]	PSL minimization, increase transmission rate and reduce motion	Optimize node location and excitation current	DPCSA
[43]	PSL minimization, increase transmission rate and reduce motion	Optimize node location and excitation current	INSGA-II and DPINSGA-II

4. CONCLUSION

In this paper, we have reviewed the CB technique with two cases static and mobile WSN. The difference is in terms of sensor node location and selection optimization. This paper also attempted to review the metaheuristic algorithms for beampattern and energy consumption optimization. A summary analysis of beampattern characteristics and properties, stability and energy consumption has been presented.

ACKNOWLEDGEMENTS

The authors would like to thank all who contributed toward making this research successful. The authors wish to express their gratitude to Ministry of Higher Education (MOHE) (Fundamental Research Grant Scheme with reference no: FRGS/1/2020/TK0/UTM/02/64 or R.J130000.7851.5F296), Research Management Center (RMC), Universiti Teknologi Malaysia for the financial support and advice for this project (UTM TDR Grant with reference no: Q.J130000.3551.06G63 and UTMFR Grant with reference no Q.J130000.2551.21H64).

APPENDIX

Table 1. Summary of beampattern optimization technique for static WSN

Reference	Objectives	Perturbation scheme	Metaheuristic algorithm
[15]	Control FNBW at desired direction and obtain null towards unintended receiver	Node selection optimization to form LAA	PSO
[16]	PSL minimization, control FNBW at desired direction and obtain null towards unintended receiver	Node selection optimization to form LAA	HLPSO
[17]	PSL minimization and reduce transmission power consumption	Node selection optimization to form RAA and optimized excitation current of selected node	IDCSA for binary part, CHCSA for continuous part and DPCSA to run both parts in parallel
[18]	PSL minimization and maximize directivity of main lobe	Node selection optimization to form LAA and RAA and optimized excitation current of selected node	CPSO
[19]	PSL minimization	Node selection optimization to form LAA	PSO-LSNA
[20]	PSL minimization and reduce computational complexity	Node selection optimization to form LAA and RAA	GDA, MA and GA
[26]	PSL minimization	Optimized excitation current of random nodes	ICSO
[27]	PSL minimization	Optimized excitation current of random nodes	CFAPSO
[28]	PSL minimization	Optimized excitation current of random nodes	BBOIMAM
[29]	PSL minimization and reduce transmission power consumption	Node selection optimization to form LAA and optimized excitation current of selected node	CSA
[30]	PSL minimization, maximize directivity of main lobe and reduce transmission power consumption	Node selection optimization to form CAA and optimized excitation current of selected node	FA
[31]	PSL minimization and reduce transmission power consumption	Node selection optimization to form CAA and optimized excitation current of selected node	CSCSO
[32]	PSL minimization and reduce transmission power consumption	Node selection optimization to form CAA and optimized excitation current of selected node	VPCSO
[33]	PSL minimization and reduce transmission power consumption	Node selection optimization to form CAA and optimized excitation current of selected node	VPCSO
[6]	Overall sidelobe reduction by maximizing directivity of main lobe	Optimized excitation current of random nodes	GA
[34]	Overall sidelobe reduction by maximizing directivity of main lobe	Optimized excitation current of random nodes	GSA
[36]	PSL minimization	Node selection optimization to form CAA	PSO
[38]	PSL minimization and reduce transmission power consumption	Node selection optimization to form CAA	BSA
[39]	PSL minimization and reduce transmission power consumption	Optimized excitation current of random nodes	BCSO
[40]	PSL minimization and maximize directivity of main lobe	Optimized excitation current and phase of random nodes	NSGA-SD
[41]	PSL minimization and reduce transmission power consumption	Optimized excitation current and phase of random nodes	FA

REFERENCES

[1] A. M. Q. K. Al-Asadi, K. S. Muttair, A. G. Wadday, and M. F. Mosleh, "Wireless body-area network monitoring with ZigBee, 5G and 5G with MIMO for outdoor environments," *Bulletin of Electrical Engineering and Informatics*, vol. 11, no. 2, pp. 893–900, Apr. 2022, doi: 10.11591/eei.v11i2.3219.

[2] A. Ghani, H. Naqvi, M. Sher, M. A. Khan, I. Khan, and A. Irshad, "Spread spectrum based energy efficient collaborative communication in wireless sensor networks," *PLOS ONE*, vol. 11, no. 7, pp. 1–24, Jul. 2016, doi: 10.1371/journal.pone.0159069.

[3] S. M. Azooz, J. H. Majeed, R. K. Ibrahim, and A. H. Ali, "Implementation of energy-efficent routing protocol within real time clustering wireless sensor networks," *Bulletin of Electrical Engineering and Informatics*, vol. 11, no. 4, pp. 2062–2070, Aug. 2022, doi: 10.11591/eei.v11i4.3916.

[4] S. Shi, S. Zhu, X. Gu, and R. Hu, "Extendable carrier synchronization for distributed beamforming in wireless sensor networks," in *2016 International Wireless Communications and Mobile Computing Conference (IWCMC)*, Sep. 2016, pp. 298–303, doi: 10.1109/IWCMC.2016.7577074.

[5] S. Jayaprakasam, S. K. A. Rahim, and C. Y. Leow, "Distributed and collaborative beamforming in wireless sensor networks: Classifications, trends, and research directions," *IEEE Communications Surveys & Tutorials*, vol. 19, no. 4, pp. 2092–2116, 2017, doi: 10.1109/COMST.2017.2720690.

[6] S. Jayaprakasam, S. K. A. Rahim, C. Y. Leow, and T. O. Ting, "Interference reduction and capacity improvement in collaborative beamforming networks via directivity optimization," in *2015 International Conference on Computer, Communications, and Control Technology (I4CT)*, Apr. 2015, pp. 332–336, doi: 10.1109/I4CT.2015.7219592.

[7] I. Dzalbs, T. Kalganova, and I. Dear, "Imperialist competitive algorithm with independence and constrained assimilation," in *2020 International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA)*, Jun. 2020, pp. 1–11, doi: 10.1109/HORA49412.2020.9152916.

[8] M. Houtinezhad and H. R. Ghaffary, "Improvement of imperialist competitive algorithm based on the cosine similarity criterion of neighboring objects," *The International Arab Journal of Information Technology*, vol. 18, no. 3, pp. 261–269, May 2021, doi: 10.34028/iajit/18/3/1.

[9] J. Kennedy and R. Eberhart, “Particle swarm optimization,” in *Proceedings of ICNN’95-International Conference on Neural Networks*, 1995, pp. 1942–1948, doi: 10.1109/ICNN.1995.488968.

[10] S. Katoch, S. S. Chauhan, and V. Kumar, “A review on genetic algorithm: past, present, and future,” *Multimedia Tools and Applications*, vol. 80, no. 5, pp. 8091–8126, Feb. 2021, doi: 10.1007/s11042-020-10139-6.

[11] P. Civicioglu, “Backtracking search optimization algorithm for numerical optimization problems,” *Applied Mathematics and Computation*, vol. 219, no. 15, pp. 8121–8144, Apr. 2013, doi: 10.1016/j.amc.2013.02.017.

[12] X. Meng, Y. Liu, X. Gao, and H. Zhang, “A new bio-inspired algorithm: Chicken swarm optimization,” in *International Conference in Swarm Intelligence*, 2014, pp. 86–94, doi: 10.1007/978-3-319-11857-4_10.

[13] X. S. Yang, “Firefly algorithm, stochastic test functions and design optimisation,” *International Journal of Bio-Inspired Computation*, vol. 2, no. 2, pp. 78–84, 2010, doi: 10.1504/IJBIC.2010.032124.

[14] X.-S. Yang and S. Deb, “Search via Lévy flights,” in *2009 World Congress on Nature & Biologically Inspired Computing (NaBIC)*, 2009, pp. 210–214, doi: 10.1109/NABIC.2009.5393690.

[15] N. N. N. A. Malik, M. Esa, S. K. Yusof, and N. M. A. Latiff, “Collaborative beamforming null-steering array for wireless sensor networks,” in *2014 IEEE 2nd International Symposium on Telecommunication Technologies (ISTT)*, Nov. 2014, pp. 316–320, doi: 10.1109/ISTT.2014.7238227.

[16] N. N. N. A. Malik, M. Esa, S. K. S. Yusof, and N. M. A. Latiff, “Intelligent linear collaborative beamforming for multi-objective radiation beampattern in wireless sensor networks,” *TELKOMNIKA Indonesian Journal of Electrical Engineering*, vol. 12, no. 10, pp. 7318–7329, Oct. 2014, doi: 10.11591/telkomnika.v12i10.6493.

[17] G. Sun *et al.*, “Energy efficient collaborative beamforming for reducing sidelobe in wireless sensor networks,” *IEEE Transactions on Mobile Computing*, vol. 20, no. 3, pp. 965–982, Mar. 2021, doi: 10.1109/TMC.2019.2955948.

[18] M. Z. Hasan and H. Al-Rizzo, “Beamforming optimization in internet of things applications using robust swarm algorithm in conjunction with connectable and collaborative sensors,” *Sensors*, vol. 20, no. 7, pp. 1–29, Apr. 2020, doi: 10.3390/s20072048.

[19] N. N. N. A. Malik, M. Esa, S. K. S. Yusof, and S. A. Hamzah, “Optimization of linear sensor node array for wireless sensor networks using particle swarm optimization,” in *2010 Asia-Pacific Microwave Conference*, 2010, pp. 1316–1319.

[20] J. D. Gorman, “The application of optimisation algorithms in antenna array beampattern synthesis,” in *2015 26th Irish Signals and Systems Conference (ISSC)*, Jun. 2015, pp. 1–5, doi: 10.1109/ISSC.2015.7163787.

[21] G. Sun, Y. Liu, G. Shen, A. Wang, Y. Zhang, and V. C. M. Leung, “Multi-objective optimization for distributed collaborative beamforming in mobile wireless sensor networks,” in *2018 IEEE Symposium on Computers and Communications (ISCC)*, Jun. 2018, pp. 752–758, doi: 10.1109/ISCC.2018.8538536.

[22] Q. Zhou *et al.*, “An improved cuckoo search algorithm for optimizing the beam patterns of the random antenna arrays,” in *2018 IEEE 4th International Conference on Computer and Communications (ICCC)*, Dec. 2018, pp. 1018–1021, doi: 10.1109/CompComm.2018.8781018.

[23] J. Li, H. Kang, G. Sun, S. Liang, Y. Liu, and Y. Zhang, “Physical layer secure communications based on collaborative beamforming for UAV networks: A multi-objective optimization approach,” in *IEEE INFOCOM 2021 - IEEE Conference on Computer Communications*, May 2021, pp. 1–10, doi: 10.1109/INFOCOM42981.2021.9488827.

[24] A. Wang, Y. Wang, G. Sun, J. Li, S. Liang, and Y. Liu, “Uplink data transmission based on collaborative beamforming in UAV-assisted MWSNs,” in *2021 IEEE Global Communications Conference (GLOBECOM)*, Dec. 2021, pp. 1–6, doi: 10.1109/GLOBECOM46510.2021.9685853.

[25] G. Sun, J. Li, Y. Liu, S. Liang, and H. Kang, “Time and energy minimization communications based on collaborative beamforming for UAV networks: A multi-objective optimization method,” *IEEE Journal on Selected Areas in Communications*, vol. 39, no. 11, pp. 3555–3572, Nov. 2021, doi: 10.1109/JSAC.2021.3088720.

[26] G. Sun, X. Zhao, S. Liang, Y. Liu, X. Zhou, and Y. Zhang, “A modified chicken swarm optimization algorithm for synthesizing linear, circular and random antenna arrays,” in *2019 IEEE 90th Vehicular Technology Conference (VTC2019-Fall)*, Sep. 2019, pp. 1–7, doi: 10.1109/VTCFall.2019.8891515.

[27] R. M. Maina, P. K. Lang’at, and P. K. Kihato, “Collaborative beamforming in wireless sensor networks using a novel particle swarm optimization algorithm variant,” *Heliyon*, vol. 7, no. 10, pp. 1–17, Oct. 2021, doi: 10.1016/j.heliyon.2021.e08247.

[28] S. Liang, Z. Fang, G. Sun, and G. Qu, “Biogeography-based optimization with adaptive migration and adaptive mutation with its application in sidelobe reduction of antenna arrays,” *Applied Soft Computing*, vol. 121, p. 108772, May 2022, doi: 10.1016/j.asoc.2022.108772.

[29] G. Sun, Y. Liu, A. Wang, J. Zhang, X. Zhou, and Z. Liu, “Sidelobe control by node selection algorithm based on virtual linear array for collaborative beamforming in WSNs,” *Wireless Personal Communications*, vol. 90, no. 3, pp. 1443–1462, Oct. 2016, doi: 10.1007/s11277-016-3403-9.

[30] G. Sun, Y. Liu, J. Zhang, A. Wang, and X. Zhou, “Node selection optimization for collaborative beamforming in wireless sensor networks,” *Ad Hoc Networks*, vol. 37, pp. 389–403, Feb. 2016, doi: 10.1016/j.adhoc.2015.08.031.

[31] G. Sun *et al.*, “A sidelobe and energy optimization array node selection algorithm for collaborative beamforming in wireless sensor networks,” *IEEE Access*, vol. 6, pp. 2515–2530, 2018, doi: 10.1109/ACCESS.2017.2783969.

[32] G. Sun, X. Zhao, S. Liang, Y. Liu, Y. Zhang, and V. C. M. Leung, “A hybrid optimization approach for suppressing sidelobe level and reducing transmission power in collaborative beamforming,” in *2019 IEEE 90th Vehicular Technology Conference (VTC2019-Fall)*, Sep. 2019, pp. 1–6, doi: 10.1109/VTCFall.2019.8891325.

[33] S. Liang *et al.*, “JSSA: Joint sidelobe suppression approach for collaborative beamforming in wireless sensor networks,” *IEEE Access*, vol. 7, pp. 151803–151817, 2019, doi: 10.1109/ACCESS.2019.2948091.

[34] R. Macharia, K. Lang’at, and P. Kihato, “Interference management upon collaborative beamforming in a wireless sensor network monitoring system featuring multiple unmanned aerial vehicles,” in *2021 IEEE AFRICON*, Sep. 2021, pp. 1–6, doi: 10.1109/AFRICON51333.2021.9570907.

[35] Y. Liu, T. Zheng, G. Sun, J. Zhang, and J. Li, “A joint optimization approach for UAV-enabled collaborative beamforming,” in *2021 IEEE Symposium on Computers and Communications (ISCC)*, Sep. 2021, pp. 1–6, doi: 10.1109/ISCC53001.2021.9631417.

[36] N. N. N. A. Malik, M. Esa, S. K. Yusof, M. K. H. Ismail, and S. A. Hamzah, “Intelligent circular collaborative beamforming array in wireless sensor network for efficient radiation,” in *2013 Asia-Pacific Microwave Conference Proceedings (APMC)*, Nov. 2013, pp. 1009–1011, doi: 10.1109/APMC.2013.6695006.

[37] C. A. Balanis, *Antenna theory: Analysis and design*, 3rd ed. Hokoben: John Wiley & Sons, 2005.

[38] N. N. A. Nazri, N. N. N. A. Malik, L. Idoumghar, N. M. A. Latiff, and S. Ali, “Backtracking search optimization for collaborative beamforming in wireless sensor networks,” *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, vol. 16, no. 4, pp. 1801–1808, Aug. 2018, doi: 10.12928/telkomnika.v16i4.9058.

[39] S. Liang, T. Feng, G. Sun, J. Zhang, and H. Zhang, “Transmission power optimization for reducing sidelobe via bat-chicken swarm optimization in distributed collaborative beamforming,” in *2016 2nd IEEE International Conference on Computer and*

Communications (ICCC), Oct. 2016, pp. 2164–2168, doi: 10.1109/CompComm.2016.7925083.
[40] S. Jayaprakasam, S. K. A. Rahim, C. Y. Leow, T. O. Ting, and A. A. Eteng, "Multiobjective beampattern optimization in collaborative beamforming via NSGA-II with selective distance," *IEEE Transactions on Antennas and Propagation*, vol. 65, no. 5, pp. 2348–2357, May 2017, doi: 10.1109/TAP.2017.2684187.
[41] R. M. Maina, K. Lang'at, and P. K. Kihato, "Concurrent sidelobe minimization and node transmission power reduction in collaborative beamforming in wireless sensor networks," in *Proceedings of the Sustainable Research and Innovation Conference*, 2022, pp. 78–83.
[42] S. Liang *et al.*, "A joint optimization approach for distributed collaborative beamforming in mobile wireless sensor networks," *Ad Hoc Networks*, vol. 106, pp. 1–12, Sep. 2020, doi: 10.1016/j.adhoc.2020.102216.
[43] G. Sun *et al.*, "Improving performance of distributed collaborative beamforming in mobile wireless sensor networks: A multiobjective optimization method," *IEEE Internet of Things Journal*, vol. 7, no. 8, pp. 6787–6801, Aug. 2020, doi: 10.1109/JIOT.2020.2983519.

BIOGRAPHIES OF AUTHORS

Najla Ilyana Ab Majid received the B.S. degree in Electrical-Electronic Engineering in 2016 and M.Sc.Eng. Degree from School of Electrical Engineering of Universiti Teknologi Malaysia (UTM). She is currently enrolled in the Ph.D. degree in School of Electrical Engineering, Universiti Teknologi Malaysia (UTM). Her current research interests are in the area of wireless communication and collaborative beamforming. She can be contacted at email: nilyana8@graduate.utm.my.

Nik Noordini Nik Abd Malik is a senior lecturer at the School of Electrical Engineering, Universiti Teknologi Malaysia (UTM), Malaysia. She received the Bachelor in Electrical Engineering (Telecommunication) from Universiti Teknologi Malaysia (UTM) in 2003. After that, she worked as a Radio Frequency R&D Electrical Engineer in Motorola Technology Ptd. in Penang, Malaysia. She then received her master degree in Master of Engineering (M.Eng.), radio frequency (RF) and Microwave Communication Engineering from University of Queensland, Australia (UQ) in 2005. She completed her Doctor of Philosophy (Ph.D.) in Electrical Engineering at Universiti Teknologi Malaysia (UTM) in 2013. Her research interests include wireless sensor network, wireless body area networks, distributed beamforming, antenna arrays, IoT smart grid, and meta-heuristic algorithms. She can be contacted at email: noordini@utm.my.

Nor Aini Zakaria received her B.Eng. degree in Electronic and System Engineering University of Takushoku, Tokyo, Japan in 2004. After graduation, she spent a year as an Industrial Engineering at Engineering Department in Pioneer Technology (M) Sdn Bhd. From 2006 she has served as a tutor in Universiti Teknologi Malaysia (UTM), before pursuing her M.Eng. (Electronics and Communications) in UTM. During her study, her research area related to biomedical engineering field, which is focused on electroencephalography signal analysis for epilepsy patient prediction. In April 2011, she started her Ph.D. study in Faculty of Biomedical Engineering in Chiba University, Chiba, Japan, before continuing her works in Department of Information Science in Nara institute of Science and Technology, Nara, Japan. She received her Ph.D. degree in September, 2019 focusing on research fall risk analysis among elderly, rehabilitation engineering. Since 2014, she is serving at the Faculty of Electrical Engineering, which currently known as School of Electrical Engineering, Faculty of Engineering, UTM. Within the Faculty of Electrical Engineering at the UTM, she teaches a few courses related to her research and elementary to the electrical and electronics curriculum. She can be contacted at email: norainiz@utm.my.