

Differential Evolution in Wireless Communications: A Review

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Hilary I. Okagbue (✉)
Covenant University, Ota, Nigeria
hilary.okagbue@covenantuniversity.edu.ng

Muminu O. Adamu
University of Lagos, Lagos, Nigeria

Timothy A. Anake
Covenant University, Ota, Nigeria

Abstract—Differential Evolution (DE) is an evolutionary computational method inspired by the biological processes of evolution and mutation. DE has been applied in numerous scientific fields. The paper presents a literature review of DE and its application in wireless communication. The detailed history, characteristics, strengths, variants and weaknesses of DE were presented. Seven broad areas were identified as different domains of application of DE in wireless communications. It was observed that coverage area maximisation and energy consumption minimisation are the two major areas where DE is applied. Others areas are quality of service, updating mechanism where candidate positions learn from a large diversified search region, security and related field applications. Problems in wireless communications are often modelled as multi-objective optimisation which can easily be tackled by the use of DE or hybrid of DE with other algorithms. Different research areas can be explored and DE will continue to be utilized in this context.

Keywords—Differential evolution, multiobjective optimisation, evolutionary computation, energy utilisation, localisation, coverage, wireless networks.

1 Evolutionary Computation

Physical phenomena are routinely studied using models. The models are sometimes complex because of different parameters that constitute them. At times, the analysis of such models is prohibitively complex and waste computation time. The insights and benefit accrual from the analysis of complex models have pushed researchers to look for a viable alternative method, which is nature [1]. Natural processes have inspired researchers in the development of computational processes, methods and algorithm that can be used to solve complex methods or to provide the best available (optimum) solution of their models. [2]. Because of the complexity of some models, optimisation became the only alternative since the models have different candidate solutions [3].

Optimisation is central to many natural processes as the method of evolution, memes and adaptation implies that organisms attempt to adjust over time to fit in optimally to their environment despite the constraints of space, search for food, shelter, and search for mates and so on. The study of these natural processes gave birth to the notion of computational intelligence of which evolutionary computation is a subfield [4].

EC is a family of iterative algorithms inspired mostly by biological evolution and are employed mostly in global optimisation [5]. In addition, is a branch of applied mathematics that deals with the global optimisation of a given function or set of functions based on some predefined criteria. Global optimisation focuses on finding the maximum or minimum of all input values while local optimisation deals with finding local minima or maxima.

In EC, an initial set of candidate solutions is generated and iteratively updated to minimise or maximise the given function [6]. Each new solution (generation) is produced by stochastically removing weaker or less desired solutions – survival of the fittest and iteratively introducing random changes until a termination criterion that guarantee a feasible solution is obtained [7]. EC techniques can produce highly optimized solutions given a wide range of constraints and complex objective function [8]. This makes EC a suitable tool for solving multi-dimensional problems and advanced optimisation [9].

The choice of EC is mainly based on the nature of the problem to be solved and the corresponding data structures. EC techniques perform well in solving higher procedure problems that are designed to find, select or search or determine a heuristic (partial search algorithm) that obtain a near optimal solution [10]. EC works with incomplete or partial, or imperfect information and limited completion capacity [11]. However, EC does not guarantee that an optimal (exact) solution will be obtained [12].

Differential evolution (DE) is one of the most widely used EC technique [13-15]. The biological processes of evolution, mutation and adaptation inspired the development of DE.

The aim of this review is to critically analyse the different areas where DE has been applied in wireless communications.

2 Differential Evolution

The basic procedure of Differential evolution (DE) is given. A population of candidate solutions (called vectors) is moved around in the search space by using the mathematical formulae defined for the objective (fitness) function to combine the positions of existing vectors from the population. If the new position of the vector is an improvement, then it is accepted and promoted to form part of the population. Otherwise, the new position is simply discarded and sometimes archived. The process is repeated t times until a satisfactory solution is discovered. Note that the algorithm does not guarantee that an optimal (exact) solution will be found.

Let $f : R^n \rightarrow R$, be the fitness function, which must be minimised, based on some equality, inequality or bounded constraints. The function maps a candidate solution in the form of vector in a given dimensional space to a real number as output,

which indicates, the fitness of the given candidate solution. The aim is to find m for which $f(m) \leq f(p)$ for all p in the search space of the given dimension, which means that the solution m is the only global minimum available.

The detailed development, component, variants, application areas and application of DE in curve fitting are presented here.

2.1 Historical development

The DE algorithm was created to be a very vital force in evolutionary computing. The first articles on DE was basically introductory [16] and it took a year later to actually demonstrate the computational efficiency of the method in an IEEE international contest built in conference [17], where it tops other EA in solving real-valued functions. Researchers were interested in the method and some papers were published to further elucidate the theory, processes and mathematics behind the method, which give birth to a clearer DE algorithm. The papers are [16] and [18-19]. Since then, DE has proven to be a force to be reckoned with, in EC. Summary of the method can be found in [20] and [21], and their references therein.

In the application of DE, the individual candidate (trial) solutions are called parameter vectors or genomes. DE utilizes difference of the parameter vectors to assess and explore the objective function landscape, which is a deviation from the other EA. The reliance of DE on difference vectors can be traced to earlier algorithms which uses difference vectors in their computation. The algorithms are Nelder-Mead algorithm [22] and the controlled random search algorithm [23].

According to [24], the reasons why DE is used by researchers as a reliable optimisation tools are listed.

1. DE is simpler and easier to implement when compared with other evolutionary algorithms. The code is easy to code with different programming languages and can easily be understood by novices.
2. The performance is better than most EC in terms of convergence, computational speed, accuracy and robustness [25]. This makes it a suitable candidate for handling unimodal, multimodal, homogenous, non-homogenous, separable and non-separable systems [26].
3. The number of control parameters (Cr, F, and NP) in DE is very few. This has helped to reduce the computational burden associated with the method [27].
4. The low space complexity of DE has been helpful in the use of DE for solving large scale, nonlinear and multi-dimensional optimisation problems.

2.2 Control parameters of the differential evolution

There are three main control parameters of the DE algorithm: the mutation scale factor F , the crossover constant Cr and the population size NP [24]. A good choice of the control parameters is necessary for the efficient execution of the DE [28]. It is recommended that for the one-dimensional case, the least population size is 4, mutation factor is set as 0.5 and the crossover constant should be adjusted between 0 and 1

and this has to be problem specific since some objective functions tend to be sensitive to the choice of the control parameters [29]. Wrong choice of these parameters will ultimately frustrate the algorithm, leading to slow convergence speed and inaccurate results [30].

2.3 Different variants of differential evolution

Since the introduction of DE, researchers have continued to propose different variants of the algorithm without necessarily altering its foundation. The nonlinear and complex nature of some problems have led researchers to push back the boundaries of DE. The different variants of DE are listed.

Differential evolution using trigonometric mutation: This was proposed by [31], aimed at speeding up the performance of DE by splitting the target vectors [32].

Differential evolution using arithmetic recombination: This comes as a departure from the traditional binomial crossover used in DE. Here, recombination can be either continuous or arithmetic. The trial vector is now expressed as a linear combination of the components from the donor and target vectors [33]. Furthermore, the coefficients of the combination can be a random variable or constant [34].

DE/rand/1/either-or algorithm: This variant of the DE algorithm was designed in such a way that the here the trial vectors that are pure mutants and those that are pure recombinants are mutually exclusive [34]. This method appears to perform better than the classical DE [25].

Opposition based differential evolution (ODE): DE usually start with some random guesses and works with no prior information about the actual optimum solution [35]. Fast convergence to the optima can be obtained simultaneously by checking the fitness of the opposite solution [36]. This has proved useful as the initial candidate solution can be chosen between the better fit options of the guess or opposite guess [37]. The process can be extended before the birth of each individual of the population.

Differential evolution with neighborhood-based mutation: This is the use of exploitation in DE which helps the algorithm to search new regions in a multi-dimensional search space. This variant of DE is effective because of two things. Firstly, the search algorithm utilizes the initial information and search towards the optima and lastly, the search algorithm will be very effective in the introduction and management of information into the population [38]. The idea behind this to prevent the search from favouring only vectors in the neighbourhood, but to extend the search to other areas.

Differential evolution with adaptive selection of mutation strategies: This variant of DE makes use of the control parameters values and self-adapted trial vector generation strategies to produce new individuals that are candidates for the optimum solution [27]. This is done by using the historical data and creating patterns that will generate the solution (unsupervised learning).

Adaptive DE with DE/current-to-pbest mutation: This uses a specific external data learning tool (archive) or algorithm to relate and interact effectively with the records of failure and success and subsequently update the control parameters with the

information. This helps in the creation of new candidate solutions to facilitate convergence and to discourage arbitrary tuning of the control parameters [26].

Hybrid Differential Evolution Algorithms: Hybrid models or algorithms in general are the combination of two or more parent algorithms to produce another one (offspring), whereby the outcome (offspring) is expected to be better than the parent algorithms. This is because; hybrid algorithms are built upon the best features of the parent algorithms. Hybridisation in DE takes three forms.

- Hybridisation with other EC algorithms: such as particle swarm optimisation [39-40], cultural algorithms [41], biogeography-based optimisation [42], earthworm [43], bacterial foraging optimisation algorithm [44-45], bare bones [46] and modified bare bones swarm optimizers [47], ant bee colony algorithm [48] and genetic algorithm [49]. Others are: tissue membrane systems [50], artificial immune systems [51], firefly algorithm [52], simulated annealing [53], neural networks [54], bat algorithm [55], krill herd algorithm [56], memetic inspired systems [57], fireworks optimisation [58], Cuckoo Search algorithm [59] and Grey Wolf optimizer [60].
- The use of local search technique (algorithms) in DE to improve the ability of the DE algorithm to make effective utilization of the information collected and to push towards obtaining the optimum solution [61]. The local search is usually adapted in the crossover stage of the DE, thereby increasing the likelihood that the optimal solutions (offspring with high fitness) will be found in small neighbourhood around the candidate solutions and reduction of fitness function evaluations. Hybridisation can also be done using neighbourhood search [62], Taguchi operator [63], clustering [64], shuffled [65] and chaotic local search, Levy flight, and Golden Section Search [66].
- Hybridisation with non-Darwinian methods: DE has been hybridized with some non-evolutionary techniques such as: black hole inspired systems [67] and gravitation search algorithm [68] and radial basis function response surface [69].
- Differential Evolution for Discrete and Binary Optimisation: DE was originally created for real value parameters. Over the years, several researchers have modified it to be utilized in tackling binary and discrete optimisation problems. This can be achieved by the following: truncating or approximating the parameter values for objective function evaluation [70] or discretisation of continuous value parameters [71], bicriteria [72] and purely binary optimisation [73]. Most applications of DE in this context are for solving job and machine scheduling problems.

Parallel differential evolution: DE can be modified to solve problems concurrently, which can be in hardware or software modes. This is done by breaking complex problems into small bits [74]. Speed, accuracy and reducing the complexity of objective function evaluation is the motivation behind parallel DE [75]. The other EC algorithm can be employed for more accuracy [76]. Parallel DE ensures that the heterogeneous nature of the optimal population is preserved after migrations. In addition, the method allows for solving optimisation problems with mixed integer and real parameter values [77].

2.4 Major strengths of the differential evolution

DE can be applied to tackle real world problems, which are unimodal/multimodal, linear/non-linear, differentiable/nondifferentiable convex/non-convex, continuous/non-continuous and symmetrical/asymmetrical in nature. These are categorized as follows:

Multiobjective optimisation (MO): Real world problems are often complex because of the composition of the different variables that are used in modelling them. These imply some problems have several criteria and objectives, which must be evaluated simultaneously in order to obtain the solution [78]. DE has proven to be well suited for tackling this type of optimisation problem. The most prominent modified version of DE that is used in solving MO problems are Pareto DE [79] and non-Pareto DE [80].

Constrained optimisation (CO): DE is very good at solving real world problems that come with conditions known as constraints. The most profound constraints are called the boundary constraint [81] or boundary value problems in numerical analysis or numerical optimisation and inequality constraints [82].

Large-scale optimisation (LSO): Most search abilities of EC algorithms failed at a very high dimension. This is due to, firstly, the complexity of the problem and the fatigue of the search strategy and secondly, the exponential increase in the solution space caused by the time it takes for the search to yield an optimum solution. This problem is present in almost all the EC algorithm of which DE is not an exception. However, experts in DE have provided means of which DE can be used to solve large scale optimisations. Some of the surveyed approaches are the fitness function refinement [83], use of chaotic systems and simplex search method [84], co-evolution [85], self-adaptive method [86], random grouping scheme [87], surrogate-assisted [88] and hybrid of co-evolution and log-normal self-adaptation [89], fuzzy adaptive method [90], strategy adaptation [27] and competition based strategy [91].

Optimisation in dynamic and uncertain environments: EC algorithms generally suffers from the uncertainties present in the optimisation problems. Those uncertainties can be time, place or measurement indexed. These uncertainties can manifest as the noisiness of the fitness function, the effect of the computing environment on the parameters, case of the fitness function being approximated and the optimal nature of the candidate solution varies over time and location. Researchers have designed different strategies to address these issues in DE environment. Intermittent varying of the scale parameter and incorporated a very good search method [92], optimisation of the objective functions that are slow and also changes with time [93] and introduction of aging mechanism to handle unstable fitness functions [94] are some of the available strategies.

Multimodal optimisation and niching: Most of objective functions encountered in real life are multimodal in nature and as such caution must be exercised in handling them because their nature connotes that several near optimal solutions may be available for them. Researchers have proposed different niching methods to tackle this issue. Niching ensures that multiple groups are maintained within the same population in order to track different optimum solutions. Some niching techniques include, but

not limited to the following: fitness sharing [95], clearing [96], crowding [97], speciation [98] and restricted tournament selection [99].

2.5 Challenges and future research areas of differential evolution

Irrespective of the advancement made in the modification of DE, the method is still faced with some challenges, some of which are presented.

- DE is still struggling to tackle objective functions that are not linearly separable [100].
- DE has been observed to fail to adequately convey the population to large distances across the solution spaces, especially when clustered population of candidate solutions are encountered [101].
- Rotation invariance remains an issue [102].
- DE is often plagued with low convergence rate due to the action of the randomized mutation operators and competition between the population and its individuals [103].
- DE is yet to convincingly prove that it can compute expensive problems better than other evolutionary computation methods [104].
- It is still very vague in DE environment; the optimum population size adaptation strategy to adopt that will yield optimum performance [105].
- Learning based approaches (supervised, reinforcement and unsupervised learning) have not been fully incorporated in DE [106].
- The problem of parameter settings indicates that more research is needed in this direction [107].
- The search continues for an EC that can guarantee 100% optimum solution.
- The following are yet to be fully developed or estimated for DE. They include: computational complexity, convergence rate estimation, expected first hitting time, the necessary and sufficient conditions that guarantee convergence and unified formulation in the theoretical development [107].
- It cannot be stated, the ranking performance of DE in solving these problems which include: multiobjective optimisation, constrained optimisation, large-scale optimisation, optimisation in dynamic and uncertain environments or multimodal optimisation.
- Finally, it can be seen that there is no automatic method of selecting a DE variant for a given problem since studies have shown that DE variants are designed to improve one aspect of DE and as such, may perform very well for a specific type of problem and perform very poor in others. Fan et al. [108] has proposed an auto-selection mechanism (ASM) in order to tackle the challenge.

3 DE in Wireless Communications

Wireless communication encompasses all processes and procedures that guarantee the transfer of information over a distance without physical connection between the

two or more points, that is, without the aid of wires, cables or any other forms of electrical conductors. The transmitted distance ranges from a few metres to thousands of kilometres. Wireless communication can be used in radio wireless technology, cellular telephony, wireless internet access, satellite and broadcast television, wireless home networking, cordless telephones and others. Wireless communication has several advantages over wired one. It is cost effective, flexible, convenient, fast, easily accessible and the probability of maintaining constant connectivity is high. However, security, coverage and other challenges are some of the issues with wireless communication.

The problems encountered in wireless communication are often NP hard. Consequently, they are modelled as a constrained optimisation problem, of which differential evolution (DE) is routinely applied to optimize the objective function resulting from the problem formulation. Minimisation or maximisation of the objective function subject to some constraints are usually the main.

A review of previous studies showed that there are six interconnecting areas where DE has been applied in wireless communications. They are: energy optimisation, improving quality of service, localisation and coverage area maximisation, updating mechanism, security application and related field applications.

3.1 Energy optimisation

Energy is required in transmission of data in wireless networks and estimation of energy consumption is important for network planning [109]. Energy consumption optimisation is a predictor of overall network performance and remains the most important constraint. DE has been used to achieve efficient energy optimisation in WSN [110] and power allocation in orthogonal frequency division multiplexing (OFDM) systems [111] thereby decreasing the gross impact of the limited available energy [112].

In order to maintain consistent energy, energy harvesting technology has been proposed to improve network throughput. DE is used to obtain the optimal throughput that will sustain consistent energy [113] and extend the lifetime of individual nodes in WSNs [114].

Delay in forwarding packets of data is a strategy to ensure efficient energy consumption, which can be achieved by providing the optimum solution of clustering and routing in wireless sensor networks (WSN) using DE [115]. Clustering ensures that data is transmitted in hierarchical order and reduces into distinct groups which helps to improve power utilization. DE has been used in clusters optimisation and an effective energy optimisation strategy [116] which guarantees network longevity [117] and optimum packet delivery ratio [118]. A hybrid of DE and simulated annealing has been used as clustering algorithm and it achieves the set goals of efficient energy utilization by reduction of loss of cluster heads and sustaining network lifetime [119].

DE was applied in the power consumption minimisation in Long Term Evolution (LTE) base stations [120].

3.2 Quality of service improvement

In improving the quality of network, it is always desirable to optimize the constraints that will yield maximum quality of service (QoS). DE has been applied to the optimisation of network coverage, power consumption, cost and human exposure minimisation to the network [121-122]. Different examples are given. They are: the case of heterogenous networks consisting of WiFi access points [123]; multi objective node deployment to ensure reliable and efficient real time performance [124-125] and lifetime maximisation [126]; optimum allocation of spectrum in wireless networks [127] and minimisation of the number of links in WSNs [128].

DE has been applied to minimize the installation cost satisfying QoS constraints in Wireless Mesh Network (WMN) [129] and minimisation of overall mobility management cost in wireless cellular networks [130]. Others are the minimisation of design and transmission costs with the aid of DE [131].

The following QoS constraints were optimised using DE; the bit error rate (BER), bandwidth, associativity-based routing (ABR), monetary cost and signal to noise ratio (SNR) [132]. For instance, a hybrid of DE and genetic algorithm was used to minimise the BER and multi-path effect of the channel thereby increasing the convergence speed [133-134]. Also, DE was used to minimize the BER in Multi-User Multiple Input Multiple Output (MU-MIMO) [135] and in general, solving the beamforming problems subjected to different variables and constraints [136]. DE was used in the optimum allocation of bandwidth in Cellular IP network, thereby improving the QoS [137].

The consequence of the optimisation is the minimisation of handovers, that is the “Ping Pong” effect [138], minimisation of end to end video reconstruction distortion [139] and resilience strategy which guarantees that a network can withstand the failure of few a nodes or links. Relay nodes is one of the resilience strategy and DE is used to find the optimum number of relay nodes that will improve connectivity and minimize network downtime [140].

Multicast routing is often preferred strategy in quality service delivery, especially in multichannel multiradio wireless mesh networks. DE has shown to be efficient in finding the optimal performance in routing [141-142], packet delivery ratio maximisation [143], delay minimisation [144] and optimum reassigning vacant channel to cognitive users without network deterioration [145]. Assignment can also take the form of allocation in download link systems [146].

Transmission rate, transmitter location and network throughput of different wireless networks have been optimized using the DE [147]. Application of DE helped in the optimisation of network throughput in networks with dynamic topological structure [148].

In order to improve network performance, DE was applied in the reporting cell problem (RCP), antenna positioning problem (APP) [149], antenna synthesis problem used in Near Field Communication (NFC) technologies [150-151] and optimisations of channel state information [152] and geometry of coupler [153].

3.3 Localisation and coverage area maximisation

Localisation in wireless networks often involves the location of sensed data in wireless sensors and devices. Location information on localisation is crucial in coverage, sensor node deployment, target tracking and routing. DE was applied as a localisation algorithm to enhance the quality of information and for convergence purposes of determining the optimal distances between nodes [154-155]. Location quality can be enhanced using DE [156-157] and specifically in base stations (BS) [158]. Apart from accuracy of location estimation, DE has shown to be useful in reducing the time complexity, thereby leading to localisation error reduction [159-160]. A further reduction of the localisation error was achieved by the hybrid of DE and Monte Carlo localisation algorithm. This is a case where the sample weight is taken as the objective function [161]. A hybrid of DE and genetic algorithm has been used as a localisation algorithm in the estimation of the location of nodes in WSN [162]. Moreover, localisation by using DE can be improved by adaptive controls over the parameters to ensure adequate tuning [163].

Generally, coverage problems in WSN are modelled as optimisation problem and can be solved using evolutionary algorithms such as DE [164]. DE is used in solving connection based localisation problem features prominently in wireless sensor networks where connections can be modelled as a nonconvex or non-convex optimisation problem which can easily be handled using DE [165].

DE has been used in finding the minimum subset of sensor nodes to cover all the targets in wireless multimedia sensor networks [166] and hence solving the targets coverage problem [167-168] and nudge redundant active nodes into sleep mode [169] or reduction of number of individual nodes which participate in non-dominated solution sorting [170]. Also available is the use of DE to optimize sensor nodes over diverse area shape, thereby increasing the coverage area [171]. Coverage radius and load balancing were optimized using DE which acts as the gateway deployment algorithm [172]. DE was used as deployment algorithm in optimisation of variables defined for directional WSNs [173].

3.4 Updating mechanism

DE algorithm can be applied as position updating mechanism where candidate positions learn from a large diversified search region such as online heuristic searching [174] and search equations for the purpose of reliable data collection [175]. The outcome is to determine the optimum path that satisfies the different quality of service (QoS) constraints in Mobile Ad Hoc Networks (MANETs) [176]. DE has been found to be a crossover strategy used as a search tool in solving optimisation problems in WSNs and superior to genetic algorithm and particle swarm optimisation [177].

DE was used to compute the fitness function in a hybrid algorithm aimed at finding the optimal path for efficient data transmission in WSN based air pollution monitoring system [178].

3.5 Security

Security issues are one of several issues facing WSN and intrusion detection system (IDS) is indispensable in the security of WSN. The aim of IDS is to detect malicious activities that affect the predefined network protocols. The multi-dimensional nature of the datasets of IDS causes data redundancy which leads to poor performance and slow speed. In order to address the data dimension issue, feature selections are often used in IDS which can be effectively optimised by the application of DE [179]. Apart from IDS, trust interference is another method of addressing security issues in WSN. DE was applied to compute trust values for each individual node in the WSN [180].

Another aspect of the security issues in WSN is the data aggregation caused by an enormous connectivity from different devices connected to the network. As a result, the network is vulnerable to security threats at the aggregated nodes. To solve the problem, DE was used to compute the trusted aggregated node among multiple nodes [181]. DE was combined with artificial immune system in the optimisation of the distribution and effectiveness of the detector generator in WSN intrusion detection [182].

The strategy of maintaining network reliability and at the same time achieving privacy preservation in WMAN can be handled using IoT-oriented offload method. DE can be used to optimize the variables while preserving privacy [183]. Random flipped is often recommended in preventing security attacks of WSN on an insecure link. Optimum flipping can be obtained using DE to minimize the fusion error and ensuring secure data transmission [184]. DE was applied to obtain optimal power schedule in wireless networks thereby, minimizing the occurrence of the denial of service (DoS) attacks [185].

3.6 Related field applications

DE is applied when the studied problem is modelled as a network with given objective function to be minimised or maximised. Another aspect is when DE is combined with other methods and applied in fields related to wireless communication. DE was applied to determine the optimal design for the appropriate pipes that fits the network distribution in water distribution system subject to cost and total loss constraints [186].

DE was applied to predict gas concentration while WSN systems were used to collect the data [187]. DE was used in energy optimisation of environmental driven WSN [188]. DE is used in path planning for unmanned underwater vehicle's (UUV) [189].

4 Conclusion

Differential evolution (DE) is one of the most widely applied evolutionary computational technique. The properties of DE outlined in this review, makes the algorithm, a favourable choice in the optimisation in wireless communications. Different variants

of DE have been used in wireless communication. Two major strengths of DE are efficient handling of multi-objective and multimodal optimisations. As seen in the review, most of the optimisation problems in wireless networks are multi-objective and multimodal in nature, of which DE was applied to obtain the desired solutions. It appears that coverage area maximisation and energy consumption minimisation are the two major areas where Differential Evolution is applied in wireless networks and communications, which was part of the submission of [190]. The networks are usually modelled as a multi-objective optimisation problem where variables are optimised using some constraints. The variables can be energy efficiency, coverage, resource allocation and so on, while the constraints can be in the form of link conflict and interference [191]. Thereafter, evolutionary algorithms, DE in this case are applied to solve the optimisation problem subject to the given constraint. Different research paths on the use of DE in wireless networks can be followed.

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7 Authors

Hilary I. Okagbue received the B.Tech degree in Industrial and Applied Mathematics from the Federal University of Technology, Owerri, Nigeria and M.Sc degree in Statistics from the University of Lagos, Akoka, Nigeria in 2007 and 2010 respectively. He is a doctoral student of the department of Mathematics, Covenant University, Ota, Nigeria. His research interests include: Quantile approximation models, non-linear statistical modeling and data analysis. He has some papers in some learned journals.

Muminu O. Adamu received the B.Sc (Hons) degree in Mathematics/Statistics, M.Sc degree in Statistics and Ph.D degree in Statistics from the University of Lagos, Akoka, Nigeria in 1995, 1998 and 2005 respectively. Since 2004, he has been a full-time lecturer and researcher in the department of Mathematics, University of Lagos, Akoka, Nigeria and now has risen to the rank of an associate professor of statistics. His research interests include: combinatorial optimization, operations research with emphasis on machine scheduling and applied statistics. He is a reviewer for the following journals: Journal of Applied Mathematics, IEEE Transactions on Evolutionary Computation and Journal of Nigerian Mathematical Society.

Timothy A. Anake received the B.Sc degree in Mathematics from the University of Uyo, Uyo, Nigeria, M.Sc degree in Mathematics from the University of Ibadan, Ibadan, Nigeria and Ph.D degree in Mathematics in Mathematics from Covenant University, Ota, Nigeria in 2000, 2004 and 2011 respectively. He was a lecturer at Igbinedion University, Okada, Nigeria from 2004 to 2006. Since 2006, he has been a full-time lecturer and researcher in the department of Mathematics, Covenant University, Ota, Nigeria and now has risen to the rank of an associate professor of numerical analysis and computation. His research interests include: numerical solutions of differential equations, nonlinear modeling of engineering systems and numerical approximation of physical systems.

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