A Framework for Power Loss Minimization by an Optimization Technique

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Abstract

The concept of power loss minimization by an optimization technique has gained wide attention in the context of distribution network loss minimization. Problems in sciences and engineering attract different shades of opinion and solution but only feasible optimal solution which shall not violate constraints imposed on the objective function will be acceptable. Distribution network loss minimization objective functions are essentially non-linear complex combinatorial problems in nature which can be better dealt with using iterative algorithms. This paper therefore seeks to present robust and effective evolutionary optimization techniques that have yielded optimal solution of optimization problems within very short execution time and minimal computational burden.

Keywords: Optimization, Loss Minimization, Algorithms, Optimal Solution, Objective function

I. INTRODUCTION

In nature and indeed engineering field and practice, problems of various forms and dimensions abound. Various solutions are formulated and applied to a given problem. The effectiveness of applied solution is dependent on a number of factors which include but not limited to; cost, practicability, safety, convenience, time among others.

In arriving at the most feasible or optimal solution to a particular problem, decisions must be taken amidst numerous options or alternatives. The measure of goodness of the alternative is described by the result anticipated which is captured by the performance index or the objective function as in [1].

Optimization of solution options or alternatives is an integral path of problem solving in scientific and engineering practice. It focuses on discovering optimum solutions to a given problem through systematic consideration of alternatives, while satisfying resources, cost and safety constraints as in [2].

In the same manner, Optimization can be said to be a tool for appraising, evaluating and weighing options or alternatives before decisions are taken with respect to a defined problem subject to prevailing constraints.

Many engineering problems are open-ended and complex. The overall objectives in these problems may be, to maximize profit through improved revenue, to minimize cost, to streamline production, to increase process efficiency etc[2]. Finding an optimum solution requires a careful consideration of several alternatives that are often compared on multiple criteria [2].

II POWER LOSS MINIMIZATION IN DISTRIBUTION NETWORK

Losses in the distribution network are largely caused by low power factor, poor voltage profile, high network (line) impedance arising from conductor of very small cross sectional area, poor joints, terminations and load imbalance among other incipient factors.

Power losses in distribution can be divided into two categories, real power loss and reactive power loss. The resistance of lines causes the real power loss, while reactive power loss is produced due to the reactive elements. Normally, the real power loss draws more attention for the utilities, as it reduces the efficiency of transmitting energy to customers as in[3].

Nevertheless, reactive power loss is obviously not less important. This is due to the fact that reactive power flow in the system needs to be maintained at a certain amount for sufficient voltage level. Consequently, reactive power makes it possible to transfer real power through transmission and distribution lines to customers.
The total real and reactive power losses in a distribution system can be calculated using equation 1 and 2.

\[
P_{\text{loss}} = \sum_{j=1}^{nbr} |I_j|^2 r_i
\]

\[
Q_{\text{loss}} = \sum_{j=1}^{nbr} |I_j|^2 x_i
\]

Where, \(nbr\) is total number of branches in the distribution radial network, \(|I_i|^2\) is the magnitude of current flow in branch \(i\), \(r_i\) and \(x_i\) are the resistance and reactance of branch \(i\), respectively. Different types of loads connected to distribution feeders also affect the level of power losses.

**A. Problem Formulation for Power System Loss Minimization**

The goal of loss minimization is to minimize the system power loss, subject to operating constraints under a certain load pattern in [4]. The objective function can be expressed as:

\[
\text{Minimize } F = \min \left[ \sum_{i=1}^{nT} \left( 40 + \left( \frac{I_i}{I_{\text{rated}}} \right)^2 \times \text{Rated Copper loss} \right) + \sum_{j=1}^{nb} I_j^2 x R_j \right]^3
\]

Subject to:

\[
[V_{\text{min}}] \leq [V_i] \leq [V_{\text{max}}]
\]

\[
[I_i] \leq [I_{j, \text{max}}]
\]

Where, \([V_i]\) is voltage magnitude of node \(i\), \([V_{\text{min}}]\) and \([V_{\text{max}}]\) are minimum and maximum node voltage magnitude, \([I_i]\) and \([I_{j, \text{max}}]\) are current magnitude and maximum current limit of branch \(j\), respectively. Also,

- \(A_0\) = Rated iron loss of power transformer
- \(I_i\) = Ampere load of incoming cable
- \(R_j\) = \(j^{th}\) branch resistances
- \(I_j\) = Current flowing through branch \(j\).
- \(nT\) = Total number of distribution transformers
- \(nb\) = Total number of candidate branches

**B. Loss Minimization Techniques**

Distribution Line Power Loss (DLPL) can be reduced using any of the following techniques: system voltage upgrade, re-conductoring, line compensation or static var compensators, re-configuration, load balancing, voltage profile improvement, distributed generation, network improvement, etc

**C. System Voltage Upgrade**

Transmission and distribution networks operate at transmission and distribution voltages of 330KV, 132KV, 66KV for transmission networks whereas 33 and 11KV are the distribution medium voltage levels in Nigeria. At tertiary distribution level, step down voltage are 33/0.400KV and 11/0.400KV for utilization level. It has been established that no-load (fixed) and load (variable) losses exists for all categories of power and distribution transformers at every voltage transformation level.

This implies that appreciable losses exist at every voltage transformation level and its value is dependent on the transformer efficiency. Losses at the voltage transformation level can be reduced if one level of voltage transformation is eliminated. In this instance, if primary load centres of distribution substations are fed at 66KV as against the present practice of 33KV, whereby 66/11KV power transformers shall be installed, voltage transformation level at 33KV can be eliminated. For a given amount of apparent power, doubling the voltagewould reduce the current by half and reduce the line loss to 25% of original[5]. Cumulative gain by this singular elimination of a level of voltage transformation can be appreciable. However, financial implication of this option is intensive.

**D. Re-conductoring**

Re-conductoring entails replacement of substandard conductors with small cross sectional areas using standard conductor cross sectional area. According to the World Bank guidelines on how to improve voltage profile, reduce losses and increase reliability of supply, the trunk route conductor should be a minimum of 100mm² Aluminium Conductor Steel Reinforced (ACSR) and spurs should be a minimum of 50mm² ACSR as contained in [6]. By ohms law, resistance is inversely proportional to area, expressed by \(R = \frac{\rho l}{A}\).

\(R\) is the resistance in (\(\Omega\)), \(\rho\) is the resistivity in (\(\Omega\)-m) of the material and \(A\) is the cross sectional area in \(\text{mm}^2\). Real power loss through the line is given by \(P\ \text{loss} = I^2R\). This implies that \(P\) loss is directly proportional to \(R\). Hence, the more the \(R\),
the more the loss for a given value of current flow and vice versa.

Re-conductoring seeks to reduce R in the network hence reduce power loss in the system. Distribution networks for different voltage levels have maximum distances they can be extended to achieve voltage drop and line losses are within minimum levels else such extension becomes unwieldy and uneconomical.

E. Line compensation or Static Var Compensators

Low power factor loads causes low voltage profile hence require reactive power to be supplied by the grid. Addition of reactive power (VAR) increases the total line current, which contributes to additional losses in the system as in [5]. Reduction in voltage below required voltage rating of an equipment causes drawing of more current from the source.

Static var compensators are usually installed at suitable locations within the network to provide the needed reactive power and hence reduce losses. Cost of static var compensators can be prohibitive when compared to the equivalent cost of loss reduction to be achieved. More so, as noted in [6], there is an optimal level of network losses when the cost of further reduction would exceed the cost of supplying the losses.

F. Re-configuration

Reconfiguration is the easiest and least costly solution to overcome the challenge of voltage drop, multiple power outages, load imbalance and high losses in the distribution network without any need to install additional equipment. Reconfiguration can be defined as the practice of imposing changes to the topology of the distribution network by appropriate closing and opening of the network switches as in [7].

Minimization of losses in a distribution network can be identified as the main objective of the reconfiguration.

Optimal distribution planning involves network reconfiguration for distribution loss minimization, load balancing under normal operating conditions and fast service restoration and minimizing the zones without power under failure conditions. It is a process of operating switches to change the circuit topology so that operating costs are reduced while satisfying the specified constraints.

Network reconfiguration is a combinatorial optimization problem because it accounts for various operational constraints in distribution systems[8]. Distribution network reconfiguration for loss reduction and load balancing is a complicated combinatorial, non-differentiable, constrained optimization problem since the reconfiguration involves many candidate-switching combinations.

G. Load Balancing

Load in the distribution network is essentially a mixture of residential, commercial and industrial loads thereby giving a varying load factor on the feeder. This implies that load (current) flow varies from time to time on different sections of the feeder. These customer categories present different load characteristics. This leads to the fact that some parts of the distribution system become heavily loaded at certain times and less loaded at other times of the day. In order to reschedule the load currents more efficiently for loss minimization, it is required to transfer the load between the feeders or substations and modify the radial structure of the distribution feeders as in [8].

G.1 Formulation of load balancing problem

An objective function for load balancing is shown to consist of two components namely: branch load balancing index and the system load balancing index.

Branch load index (LBj) is defined as a measure of how much a branch can be loaded without exceeding the rated capacity of that branch. The essence is to optimize the branch load indices so that the system load balancing index is minimized. That is to say that, all the branch load balancing indices are set to be more or less the same value and are also nearly equal to the system load balancing index.

The load balancing problem is formulated in the form of branch load balancing and system load balancing indices contained in [8] as

\[
LB_j = \frac{S(j)}{S(j)_{max}}
\]

The system load balancing index,

\[
LB_{sys} = \frac{1}{n_b} \sum_{j=1}^{n_b} \frac{S(j)}{S(j)_{max}}
\]
Where, \( nb \) is the total number of branches in the system
\( S(j) \) is apparent power of branch \( j \)
\( S(j)_{\text{max}} \) is maximum capacity of branch \( j \)

Objective function:
\[
\text{Minimize } F = \frac{1}{nb} \sum_{j=1}^{nb} \frac{S(j)}{S(j)_{\text{max}}}
\]

The system load balancing index will be minimized when the branch load indices are optimized by rescheduling the loads. In effect, all the branch load balancing indices, \( (LBj) \) are made approximately equal to each other and also closely approximate to the system load balancing index \( (LBsys) \).

Representing mathematically:
\[
\frac{S(1)}{S(1)_{\text{max}}} = \frac{S(2)}{S(2)_{\text{max}}} = \frac{S(j)}{S(j)_{\text{max}}} = \ldots = \frac{S(n)}{S(n)_{\text{max}}} = \frac{1}{nb} \sum_{j=1}^{nb} \frac{S(j)}{S(j)_{\text{max}}}
\]

The conditions taken into consideration are:

i. System loss must be minimized
ii. The voltage magnitude of each node must be within permissible limits \( \pm 6\% \). Of the nominal system voltage.

i.e. \( |V_{\text{min}}| \leq |V| \leq |V_{\text{max}}| \)

Current capacity of each branch, \( |I| \leq |I_{\text{max}}| \)

When the load balancing index, \( LBj \) of the branch is equal to 1, then the condition of that branch will become critical and the branch rated capacity will be exceeded if it is greater than 1. The system load balancing index, \( LBsys \) will be low if the system is lightly loaded and its value will be closer to zero, and the individual branch load balancing indices will also be low.

If the loads are unbalanced, the load balancing indices of individual branches will differ widely, whereas, the balanced load will make the load balancing indices of all the branches nearly equal. It is not practically possible to make all the branch load balancing indices, \( LBj \) exactly equal. However, it is possible that by reconfiguration the load balancing indices of the branches will be adjusted, and hence the load balancing in the overall system improved [8].

H. Voltage Profile Improvement

Heavily loaded and lengthy radial distribution networks suffer appreciable low voltages mostly at nodes far removed from source of supply. Loads connected at these nodes tend to draw large value of current needed to provide the required power rating or output of the connected equipment.

Drawing of large value of current through a high resistance path is a source of power loss in a distribution network. Networks with remarkable poor voltage profile contribute meaningfully to the networks loss level. Loads that are of poor power factor (inductive or reactive loads) contribute substantially to low voltage profile associated with such network.

The distribution systems are usually radial, unbalanced and have a high R/X ratio compared to transmission systems, which results in high voltage drops and power losses in the distribution feeders (networks). The vital tasks in the distribution system are reduction of power losses and improvement of the system voltage profile [9].

Installation of Automatic Voltage Boosters or voltage compensators, Shunt and series capacitors suitably located at optimal locations in the network have the capacity to improve the voltage profile of the network hence reduce the associated losses.

Determination of suitable or optimal location of voltage compensating equipment in a network is typically an optimization problem. More so, appropriately adjusting the medium voltage and distribution transformer tap position to reflect the system line voltages has the capacity to improve the voltage profile of networks that are fairly balanced, suitably loaded and route length not over stretched or within optimal length.

Achieving these options is capital intensive and compromise should be reached between loss minimization, capital investment and non-violation of imposed voltage limits constraints.

I. Distributed Generation

The concept of Distributed Generation arose out of efforts at addressing the power quality and reliability problems to electricity end users. In many instances, it is either the voltage profile is poor to the extent that equipment rated name plate voltage is hardly reached hence creating serious
operational problem or frequent outages and increased loss level is pronounced.

Challenges of establishing more power stations to ensure maintenance of grid integrity and extension to remote locations is rife in developing economies like Nigeria. Distributed Generation therefore becomes very handy in addressing power supply reliability and loss reduction in distribution networks.

Distributed Generation [DG] is any small-scale electrical power generation technology that provides electric power at or near the load site; it is either interconnected to the distribution system, directly to the customer’s facilities, or both [10].

DG causes a significant positive impact in electric power loss reduction due to its proximity to the load centres when it is optimally located. DG allocation is similar to capacitor allocation in loss minimization. The main difference is that the DG units cause positive impact on both the active and reactive power need of the distribution network, while the capacitor banks only have impact in the reactive power flow.

In feeders with high losses, a small amount of DG of capacity (10-20% of the feeder load) strategically allocated could cause a significant reduction of losses [10]. Optimal location of Distributed Generation entails positioning of the DG where its impact on loss reduction and system reliability is maximum. However, huge capital investment is required to implement Distributed Generation but may present a viable alternative when other factors as reliability and expansion schemes other than loss reduction are considered.

J. Network Improvement

In developing countries like Nigeria, sight of badly maintained and constructed distribution networks are common. A large capacity transformer of say rating 500KVA can be seen radiating out three sections of distributor feeds to customers of diverse load requirements. Length of such distributors runs many kilometres same as 11kv networks spanning over 45km route length. These are obvious sources of losses in the distribution network.

The following network improvement initiatives can be adopted as loss reduction measures;

1. High Voltage Distribution System (HVDS) as against Low Voltage Distribution System; whereby medium to low voltage line ratio of the distribution network is seriously reduced. Lower rating distribution transformers are located very close to the customers thereby reducing the run length of distributors and service cables. When run lengths are reduced, resistance of the network is reduced hence a reduction in power losses is achieved with maintenance of healthy voltage profile.

2. Decongestion of badly joined and clustered connections along the distribution network and applying of appropriate connecting devices, connectors and termination accessories. Such poor connections are sources of hot spots that generate so much heat and snapping of conductors with its attendant safety concerns.

3. Replace burnt and weak power distribution boxes e.g. feeder pillars (boxes), load switches, units and links with clear evidence of burnt including the bus bars.

4. Use appropriate service cable, bimetals, and conductors of appropriate sizes for load connections.

5. Replace obsolete and over aged distribution equipment and panels.

6. Ensure appropriate sizing of transformers with respect to the load in a given area and use adequate secondary cables and lugs for termination

III LOSS MINIMIZATION BY AN OPTIMIZATION TECHNIQUE

The loss reduction techniques enumerated above can be applied for distribution loss minimization but the options adopted are guided by the major identified cause(s) of losses in the network.

In general, solution for loss minimization seeks to provide the optimal approach at achieving the target goal. This goes to show that numerous options abound which therefore requires that optimization is necessary at arriving at the optimal solution.
There exists good number of optimization approach but decision usually favours optimization technique that poses less computational burden but presents feasible and cost effective solution.

Optimization problems for loss reduction are not linear but complex combinatorial and non-differentiable optimization problems. Due to its nonlinearity, a nonlinear approach is therefore required to tackle them. Computer algorithms of different forms and complexities have been developed to aid computation in finding optimal solution.

A. Optimization Techniques

Metaheuristic and evolutionary algorithms at various levels have been developed and applied in determining the optimal solutions to engineering problems including loss reduction in distribution networks.

The following belong to the family of metaheuristic algorithms[11];

1. Genetic Algorithm
2. Tabu Search
3. Simulated Annealing among others

In the family of evolutionary algorithms, we have;

4. Particle Swarm Optimization Algorithm
5. Plant Growth Optimization Algorithm
6. Bacteria Foraging Optimization Algorithm

Most current algorithms with proven better efficiencies in terms of execution time and error margins are;

i. Plant Growth Simulation Algorithm (PGSA)
ii. Bacteria Foraging Optimization Algorithm (BFOA)
iii. Particle Swarm Optimization Algorithm

B. Plant Growth Simulation Algorithm

The plant growth simulation algorithm is a bionic random algorithm which characterizes the growth mechanism of plant phototropism. It looks at the feasible region of integer programming as the growth environment of a plant and determines the probabilities to grow a new branch on different nodes of a plant according to the change of the objective function, and then makes the model, which simulates the growth process of a plant, rapidly growing towards the light source (global optimum solution)as contained in [8].

B.1 Growth Laws of a Plant

The following facts have been proved by the biological experiments stated in [8].

1. In the growth process of a plant, the higher the morphactin concentration of a node, the greater the probability to grow a new branch on the node.
2. The morphactin concentration of any node on a plant is not given beforehand and is not fixed; it is determined by the environmental information of the node, and the environmental information of a node depends on its relative position on the plant. The morphactin concentrations of all nodes of a plant are allotted again according to the new environment information after it grows a new branch.

B.2 Probability Model of Plant Growth

By simulating the growth process of plant phototropism, a probability model is established. In the model, a function \( g(Y) \) is introduced for describing the environment of the node \( Y \) on a plant. The smaller the value of \( g(Y) \), the better the environment of the node \( Y \) for growing a new branch. The main outline of the model is as follows:

A plant grows a trunk \( M \) from its root \( B_0 \). Assuming there are \( k \) nodes \( B_{M1}, B_{M2}, B_{M3} \ldots \ldots B_{Mk} \) that have better environment than the root \( B_0 \) on the trunk \( M \), which means the function \( g(Y) \) of the nodes \( B_{M1}, B_{M2}, B_{M3} \ldots \ldots B_{Mk} \) and \( B_0 \) satisfy \( g(B_{Mi}) < g(B_0) \) (\( i = 1, 2, 3\ldots k \)), then the morphactin concentrations \( C_{M1}, C_{M2}, C_{M3} \ldots \ldots C_{Mk} \) of the nodes \( B_{M1}, B_{M2}, B_{M3} \ldots \ldots \) \( B_{Mk} \) can be calculated using,

\[
C_{Mi} = \frac{g(B_0) - g(B_{Mi})}{\Delta_{1}} \text{ (i = 1, 2, 3...k)}
\]

\( \Delta_{1} = \sum_{i=1}^{k} (g(B_0) - g(B_{Mi})) \)

![Figure 1: Morphactin Concentration State Space](image-url)
The significance of equation (7) is that the morphactin concentration of a node is not dependent on its environmental information but also depends on the environmental information of the other nodes in the plant, which really describes the relationship between the morphactin concentration and the environment.

From equation (7), we can derive
\[ \sum_{i=1}^{k} C_{Mi} = 1, \]
which means that the morphactin concentrations CM1, CM2, CM3 ……… CMk of the nodes BM1, BM2, BM3 ………. BMk form a state space shown in Figure 1. Selecting a random number \( \beta \) in the interval \([0, 1]\), \( \beta \) is like a ball thrown to the interval \([0, 1]\) and will drop into one of CM1, CM2, CM3 ………. CMk in Figure 1, then the corresponding node that is called the preferential growth node will take priority of growing anew branch in the next step. In other words, BMT will take priority of growing a new branch if the selected \( \beta \) satisfies
\[ 0 \leq \beta \leq \sum_{i=1}^{T} CM_{i} \quad (T = 1) \text{ or } \sum_{i=1}^{T-1} CM_{i} < \beta \leq \sum_{i=1}^{T} CM_{i} \quad (T = 2, 3, \ldots k). \]

For example, if random number \( \beta \) drops between an interval \([1, 2]\), which means \( \sum_{i=1}^{k} C_{Mi} < \beta \leq \sum_{i=1}^{k} C_{Mi} \), then the new branch \( m \) will grow at node 2.

C. Particle Swarm Optimization Algorithm (PSOA)

Particle swarm optimization is a heuristic global optimization method put forward originally by J. Kennedy and E Berhart in 1995[10]. It is developed from swarm intelligence and is based on the research of bird and fish flock movement behaviour. While searching for food, the birds are either scattered or go together before they locate the place where they can find food. While the birds are searching for food from one place to another, there is always a bird that can smell the food very well, that is, the bird is perceptible of the place where the food can be found, having the better food resource information. Because they are transmitting the information, especially the good information at any time while searching the food from one place to another, conducted by the good information, the birds will eventually flock to the place where food can be found. As far as particle swarm optimization algorithm is concerned, solution swarm is compared to the bird swarm, the birds’ moving from one place to another is equal to the development of the solution swarm, good information is equal to the most optimist solution, and the food resource is equal to the most optimist solution during the whole course.

In the basic particle swarm optimization algorithm, particle swarm consists of “n” particles, and the position of each particle stands for the potential solution in d-dimensional space. The particles change its condition according to the following three principles:

1. To keep its inertia
2. To change the condition according to its most optimist position
3. To change the condition according to the swarm’s most optimist position.

The position of each particle in the swarm is affected both by the most optimist position during its movement(individual experience) and the position of the most optimist particle in its surrounding (near experience).

When the whole particle swarm is surrounding the particle, the most optimist position of the surrounding is equal to the one of the whole most optimist particle; this algorithm is called the whole PSO. If the narrow surrounding is used in the algorithm, this algorithm is called the partial PSO.

Each particle can be shown by its current speed and position, the most optimist position of each individual and the most optimist position of the surrounding. In the partial PSO, the speed and position of each particle change according the following equality expression [10].

\[ V_{id}^{k+1} = V_{id}^{k} + C_{1}r_{1}^{k}(pbest_{id}^{k} - x_{id}^{k}) + C_{2}r_{2}^{k}(gbest_{d}^{k} - x_{id}^{k}) \]

\[ x_{id}^{k+1} = x_{id}^{k} + V_{id}^{k+1} \]

In this equality, \( V_{id}^{k} \) and \( x_{id}^{k} \) stand for separately the speed of the particle “i” at its “k” times and the d-dimension quantity of its position; \( pbest_{id}^{k} \) represents the d-dimension quantity of the individual “i” at its most optimist position at its “k” times. \( gbest_{d}^{k} \) is the d-dimension quantity of the swarm at its most optimist position.
In order to avoid particle being far away from the searching space, the speed of the particle created at its each direction is confined between $V_{\text{emax}}$ and $V_{\text{dmax}}$. If the number of $V_{\text{dmax}}$ is too big, the solution is far from the best, if the number of $V_{\text{dmax}}$ is too small, the solution will be the local optimism; $c_1$ and $c_2$ represent the speeding figure, regulating the length when flying to the most particle of the whole swarm and to the most optimist individual particle. If the figure is too small, the particle is probably far away from the target field, if the figure is too big, the particle will maybe fly to the target field suddenly or fly beyond the target field. The proper figures for $c_1$ and $c_2$ can control the speed of the particle’s flying and the solution will not be the partial optimism. Usually, $c_1$ is equal to $c_2$ and they are equal to 2; $r_1$ and $r_2$ represent random fiction, and 0-1 is a random number.

The Particle Swarm Optimization algorithm though have wide application in science and engineering problems, but still have the inability of being used in scattering and optimization problems as well as problems of non-coordinate systems like the solution to the energy field and the moving rules of the particles in the energy field.

POS has no systematic calculation method and it has no definite mathematical foundation [10]. Particle swarm optimization is a new heuristic optimization method based on swarm intelligence. Compared with the other algorithms, the method is very simple, easily completed and it needs fewer parameters, which made it fully developed. However, the research on the PSO is still at the beginning, a lot of problems are to be resolved [10].

D. Bacterial Foraging Optimization Algorithm (BFOA)

Bacteria Foraging Optimization Algorithm (BFOA), proposed by Passino, is a new development to the family of nature-inspired optimization algorithms. BFOA [13] is inspired by the social foraging behaviour of Escherichia-coli, E-coli. The underlying biology behind the foraging strategy of E.coli is emulated in an extraordinary manner and used as a simple optimization algorithm. Jason B. [14], The Bacteria Foraging Optimization Algorithm BFOA belongs to the field of bacteria optimization algorithms and swarm optimization and more broadly to the fields of computational intelligence and metaheuristics.

D.1 Steps of Bacteria Foraging Algorithm

There are four steps in Bacteria Foraging Algorithm after the search strategies like swimming and tumbling. They are [12, 14, 15]:

i. Chemotaxis
ii. Reproduction
iii. Elimination and dispersal
iv. Swarming

D.2 Chemotaxis

Chemotaxis process is the characteristics of movement of bacteria in search of food and consists of two processes namely swimming and tumbling. A bacterium is said to be ‘swimming’ if it moves in a pre-defined direction and tumbling if moving in an altogether different direction. When a bacterium meets a favourable environment (rich in nutrients, and noxious free), it will continue swimming in the same direction. When it meets an unfavourable environment, it will tumble, i.e. change direction. Let $j$ be the index of the chemotactic step, $k$ be the reproduction step and $l$ be the elimination dispersal event. Let $S$, be the total number of bacteria in the population, and a bacterium position represents a candidate solution of the problem and information of the $i$-th bacterium with a d-dimensional vector represented as $\theta = [\theta_1, \theta_2, \theta_3, \ldots, \theta_n], i = 1, 2, 3, \ldots, S$. Suppose $\theta(i,j,k,l)$ represents $i$-th bacterium at the $j$-th chemotactic, $k$-th reproduction step, and $l$-th elimination and dispersal step. Then in computational chemotaxis, the movement of the bacterium may be represented by $\theta'(j+1, k, l) = \theta(j, k, l) + C(i)\Phi(j) - 10$

Where $C(i)$ is the size of the step taken in the random direction specified by the tumble (run length unit), and $\Phi(j)$ is in the random direction specified by the tumble. The position of the bacteria in the next chemotactic step after a tumble is given by:

$\theta'(j+1, k, l) = \theta(j, k, l) + C(i) \frac{4\Phi}{\sqrt{9\Phi^2 + 44}}$

If the health of the bacteria improves after the tumble, the bacteria will continue to swim to...
the same direction for the specified steps or until the health degrades.

Similarly, suppose we want to find the minimum of \( J(\theta), \theta \in \mathbb{R} \), where we do not have measurements, or an analytical description, of the gradient \( \hat{V} J(\theta) \). Here, \([15]\) we use ideas from bacteria foraging to solve this “non-gradient” optimization problem.

First, suppose that \( \theta \) is the position of a bacterium and \( J(\theta) \) represents the combination of attractants and repellents from the environment, which for example, \( J(\theta) < 0 \), \( J(\theta) = 0 \) and \( J(\theta) < 0 \) representing that the bacterium at location \( \theta \) is in nutrient-rich, neutral, and noxious environments, respectively.

Basically, chemotaxis is a foraging behaviour that implements a type of optimization where bacteria try to climb up the nutrient concentration (find lower and lower values of \( J(\theta) \) and avoid noxious substances and search for ways out of the neutral media (avoid being at positions of \( \theta \) where \( J(\theta) \geq 0 \) \([14]\). Chemotaxis, \([13]\) is the process which simulates the movement of an E.coli cell through swimming and tumbling via flagella.

Biologically, an E.coli bacterium can move in two different ways – it can swim for a period of time in the same direction or it may tumble and alternate between these two modes of operation for the entire lifetime.

**D.3 Reproduction**

The health status (fitness) of each bacterium is calculated after each completed chemotaxis process. The sum of the cost function is

\[
J_{\text{health}}^t = \sum_{j=1}^{Nc} P_{i,j,k,l}^{t} \tag{12}
\]

Where \( Nc \) is the total number of steps in a complete chemotaxis process. Locations of healthier bacteria represent better sets of optimization parameters. To further speed up and refine the search, greater number of bacteria are required to be placed at these locations in the optimization domain. This is done in the reproduction step. The healthier half of bacteria (with minimum value of cost function) are allowed to survive, while the other half die.

The least healthy bacteria eventually die while each of the healthier bacteria (those yielding lower value of the objective function) asexually split into two bacteria, which are then placed in the same location. An interesting group behaviour has been observed for several motile species of bacteria including E.coli and salmonella typhimurium, where intricate and stable spatio-temporal patterns (swarms) are formed in semi-solid nutrient medium \([12]\).

A group of E.coli cells arrange themselves in a travelling ring by moving up the nutrient gradient when placed amidst a semi-solid matrix with a single nutrient chemo-effector. The cells when stimulated by a high level of succinate, release an attractant aspartate, which helps them to aggregate into groups and thus move as concentric patterns of swarms with high bacterial density. Reproduction as described here keeps the swarm size constant.

**D.4 Elimination and dispersal**

The chemotaxis provides a basis for local search, and the reproduction process speeds up the convergence, which has been simulated by the classical BFO. While to a large extent, chemotaxis and reproduction alone are not enough for global optima searching, since bacteria may be stuck around the initial positions or local optima, it is possible for the diversity of BFO to change either gradually or suddenly to eliminate the accident of being trapped into the local optima.

In BFO, the dispersion event happens after a certain number of reproduction processes. Then some bacteria are chosen to be killed according to a preset probability or moved to another position within the environment.

Gradual or sudden changes in the local environment where a bacterium population lives may occur due to various reasons e.g. a significant local rise of temperature may kill a group of bacteria that are currently in a region with a high concentration of nutrients gradients. Events can take place such that all the bacteria in a region are killed or a group is dispersed into a new location. To simulate this phenomenon in BFOA some bacteria are liquidated at random with a very small probability while the new replacements are randomly initialized over the search space.
D.5. Swarming

Bacteria exhibits swarm behaviour i.e. healthy bacteria try to attract other bacteria so that together they reach the desired location (solution point) more rapidly. The effect of swarming is to make the bacteria congregate into groups and move as concentric patterns with high bacterial density. E. coli bacterium has a specific sensing, actuation, and decision-making mechanism.

As each bacterium moves, it releases attractant to signal other bacteria to swarm towards it. Meanwhile, each bacterium releases repellent to warn other bacteria to keep a safe distance between each other. BFO simulates this social behaviour by representing the combined cell-to-cell attraction and repelling effect can be modelled as:

$$J_{cc}(\theta, p(j, k, l)) = \sum_{i=1}^{s} J_{cc}(\theta, \theta^{i}(j, k, l)) = \sum_{i=1}^{s} \left[ \sum_{m} \left( \sum_{k} \left( \sum_{j} \left( \sum_{l} \right) \right) \right) \right] + \sum_{m} \left[ \sum_{k} \left( \sum_{j} \left( \sum_{l} \right) \right) \right]$$

Here, ‘it discovers a new domain’ means this bacterium registers a fitness improvement beyond a certain precision from the last generation to the current. Following criterion – 1, the bacterium’s behaviour will self-adapt into exploitation state.

ii. Criterion – 2: If the bacterium’s current fitness is unchanged for a number of consecutive generations, then this bacterium’s run-length unit is augmented and this bacterium enters exploration state. This situation means that the bacterium searches an unpromising domain.

Table 1 shows the result of improved BFO algorithm using a test-suite of five well known benchmark functions as shown in [17].

Table 1 Result of improved BFO Algorithm using a test-suite of five well known benchmark functions contained in [17].

<table>
<thead>
<tr>
<th>Function</th>
<th>Dimension</th>
<th>Max. of FE’s</th>
<th>Mean Best Values (Standard Deviation)</th>
</tr>
</thead>
<tbody>
<tr>
<td>IBFO</td>
<td>PSO</td>
<td></td>
<td></td>
</tr>
<tr>
<td>f1</td>
<td>5 x 10^4</td>
<td>0.0416 (0.0046)</td>
<td>0.5950 (0.5623)</td>
</tr>
<tr>
<td></td>
<td>5 x 10^5</td>
<td>0.8841 (0.3221)</td>
<td>1.2160 (0.9254)</td>
</tr>
<tr>
<td>f2</td>
<td>5 x 10^4</td>
<td>1.7952 (0.7145)</td>
<td>4.3573 (1.3297)</td>
</tr>
<tr>
<td></td>
<td>5 x 10^5</td>
<td>8.4228 (0.3259)</td>
<td>12.3243 (10.8654)</td>
</tr>
<tr>
<td>f3</td>
<td>5 x 10^4</td>
<td>1.7952 (0.3259)</td>
<td>1.0322 (0.0237)</td>
</tr>
<tr>
<td></td>
<td>5 x 10^5</td>
<td>8.4228 (0.1683)</td>
<td>12.3243 (1.8833)</td>
</tr>
<tr>
<td>f4</td>
<td>5 x 10^4</td>
<td>1.9625 (0.2835)</td>
<td>3.4561 (2.6632)</td>
</tr>
<tr>
<td></td>
<td>5 x 10^5</td>
<td>8.4228 (1.6559)</td>
<td>17.5249 (9.8962)</td>
</tr>
<tr>
<td>f5</td>
<td>5 x 10^4</td>
<td>0.0010 (0)</td>
<td>0.2612 (0.0216)</td>
</tr>
<tr>
<td></td>
<td>5 x 10^5</td>
<td>0.1927 (0.0252)</td>
<td>0.3729 (0.0346)</td>
</tr>
</tbody>
</table>

Average and standard deviation (in parenthesis) of the best – of – run independent runs tested on five benchmark functions.

Legend:

FE = Function Evaluation, IBFO = Improved Bacteria Foraging Optimization, BFO = Bacteria Foraging Optimization, PSO = Particle Swarm Optimization.

The benchmark functions are [15]:

1. Rosenbrock function
$$f_1(x) = \sum_{i=1}^{n-1} [100(x_{i+1} - x_i^2)^2 + (1 - x_i)^2]$$

The function has a global optimum value of 0, when $$x_{i=1},(i=1,2,\ldots,n-1); x \in [-2.048,2.048]$$

D.6 Fitness indicator (Health)

As suggested by Chen et al. [14], each bacterium in the colony has to permanently maintain an appropriate fitness between exploration and exploitation starts by varying its own run-length unit adaptively. The adaptation of the individual run-length unit is done by taking into account the decision indicator of fitness improvement (health).

The criteria that determine the adjustment of individual run-length unit and the entrance of the states (i.e., exploitation and exploration) are as follows:

i. Criterion – 1: If the bacterium discovers a new promising domain, the run-length unit of this bacterium is adapted to another smaller one.
2. Rotated hyper-ellipsoid function
   \[ f_2(x) = \sum_{j=1}^{n} (x_j)^2 \]
   The function has a global minimum value of 0, when
   \[ x_i = 0 \quad (i = 1, 2, \ldots, n) \]
   and the value is 0 when \( x \in [-65.536, 65.536] \).

3. Ackley function
   \[ f_3(x) = -a x e^{-b \sqrt{\frac{1}{n} \sum_{i=1}^{n} x_i^2}} - \frac{e^{\frac{1}{n} \sum_{i=1}^{n} \cos(c x_i)}}{n} + a + e \]
   Its global minimum is at \( x_i = 0 \quad (i = 1, 2, \ldots, n) \)
   and the value is zero where \( x \in [-32.768, 32.768] \).

4. Rastrigrini function
   \[ f_4(x) = 10 n + \sum_{i=1}^{n} (x_i^2 - 10 \sin(2 \pi x_i)) \]
   Its global minimum is at \( x_i = 0 \quad (i = 1, 2, \ldots, n) \)
   and the value is 0, where \( x \in [-5.12, 5.12] \).

5. Griewank function
   \[ f_5(x) = \sum_{i=1}^{n} \frac{x_i^2}{4000} - \prod_{i=1}^{n} \cos \left( \frac{x_i}{\sqrt{i}} \right) + 1 \]
   Its global minimum is at \( x_i = 0 \quad (i = 1, 2, \ldots, n) \)
   and the value is 0, where \( x \in [-600, 600] \).

Comparison results of different metaheuristic algorithms used on IEEE 33-bus radial network is shown in table 2 below.

<table>
<thead>
<tr>
<th>S/No</th>
<th>Method</th>
<th>Open Switches</th>
<th>Power Loss (KW)</th>
<th>Percentage (%) of Loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Proposed BFOA</td>
<td>7,9,14,32,37</td>
<td>135.67</td>
<td>33.07</td>
</tr>
<tr>
<td>2</td>
<td>Rao et al (Harmony Search Algorithm)</td>
<td>7,10,14,36,37</td>
<td>138.06</td>
<td>31.89</td>
</tr>
<tr>
<td>3</td>
<td>Zhu et al (Refined Genetic Algorithm)</td>
<td>7,9,14,32,37</td>
<td>139.53</td>
<td>31.16</td>
</tr>
<tr>
<td>4</td>
<td>Shirmohammadi and Hong</td>
<td>7,10,14,33,37</td>
<td>141.54</td>
<td>30.17</td>
</tr>
</tbody>
</table>

IEEE 33-bus radial distribution network reconfiguration used to simulate metaheuristic algorithms in distribution network loss minimization is shown in figure 2 below.

Figure 2 An IEEE 33-bus radial distribution network after reconfiguration as contained in [18]

Different optimization algorithms listed in table 2 above have been used on the network of figure 2 to determine level of loss reduction achieved after reconfiguration with switch numbers listed kept in open position. Performance of the various algorithms were indicated in percentages against each approach. It can be seen clearly that BFOA achieves 2 – 3% more efficient than others [18].

It has higher efficiency and good convergence characteristics comparatively. This attribute has made BFOA very robust, elaborate, efficient and adaptable to wide range of real life optimization problems including large scale network as can be seen in electric power distribution system.

The generalized flow chart depicting the operational steps followed in the simulation of bacteria foraging optimization technique is shown if figure 3 below.
However, its potentials for higher efficiency is still high speed of convergence in comparison with applied deve optimiza
tion problems. It is the most recent solving complex non
proved more robust, elaborate and efficient in
problems but BFOA optimization techniques have
explored widely in science and engineering
research works based on evolutionary artificial
intelligence algorithm in optimization have also
its calculation has been posited. Some recent
these approaches have been explored widely in science and engineering problems but BFOA optimization techniques have
proved more robust, elaborate and efficient in
solving complex non – linear combinatorial
optimization problems. It is the most recent
development in evolutionary artificial intelligence
applied in real life optimization problems. It has
high speed of convergence in comparison with
other evolutionary artificial intelligence algorithms.
However, its potentials for higher efficiency is still
of interest among researchers.

INFORMATION TECHNOLOGY TRENDS

CONCLUSION

In this paper loss minimization by optimization
techniques have been x-rayed and a framework for
its calculation has been posited. Some recent
research works based on evolutionary artificial
intelligence algorithm in optimization have also
been presented. These approaches have been
explored widely in science and engineering
problems but BFOA optimization techniques have
proved more robust, elaborate and efficient in
solving complex non – linear combinatorial
optimization problems. It is the most recent
development in evolutionary artificial intelligence
applied in real life optimization problems. It has
high speed of convergence in comparison with
other evolutionary artificial intelligence algorithms.
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References

1. K.P. Chong, H.Z. Stanislaw; An Introduction to
Optimization; A Wiley Interscience Publication, second
3. Y. Al-Mahroqi, I.A. Metwally, A. Al-Hinai, and A. Al-
Badi; Reduction of Power Losses in distribution systems,
World Academy of Science, Engineering and Technology ,
Vol 63, 2012
4. P. Sarang, J.G. Ghodekar, Reduction of Power Loss of
Distribution System by Distribution Network
Management, International Journal of Multidisciplinary
5. H.Inan, J. Batson, System Loss Reduction, Tech
Advantage, March 2014, Mark Scheibe Maquoketa Valley
Electric Cooperation, hakan.inan@leidos.com,
joni.s.batson@leidos.com
6. P. Kundur, Power System Stability and Control, Tata
7. M. Rohani, H. Tahatabae, A. Rohani, Reconfiguration for
Loss Reduction in Distribution Network using Hybrid PSO
algorithm and Fuzzy Logic, Bulletin of Environment,
Pharmacology of Life Sciences Bull. Env. Pharmacol. Life
8. P. V. V. Rama Rao and S. Sivanagaraju, Radial
Distribution Network Reconfiguration for Loss Reduction
and Load Balancing using Plant Growth Simulation
Algorithm, International Journal on Electrical Engineering
and Informatics - Volume 2, Number 4, 2010
9. M. Natarajan, R. Balamurugan and L.
Lakshminarasimman, Optimal Placement and Sizing of
DGs in the Distribution System for Loss Minimization and
Voltage Stability Improvement using CABC, International
Journal on Electrical Engineering and Informatics – Vol.7,
No. 4, December 2015.
10. Qingbai Bai, Analysis of Particle Swarm Optimization
Algorithm, Computer and Information Science, vol. 3,
No 1; www.ecscenet.org/cis
11. A.A Ahmed Esmin, G. Lambert-Torres, Application of
Particle Swarm Optimization to Optimal Power Systems,
International Journal of Innovative Computing,
Information and Control. Vol 8, No 3 (A), March 2012.
12. K.S. Kumar, T.Jayabarathi, Power System Reconfiguration
and Loss Minimization for a distribution systems using
Bacteria Foraging Optimization Algorithm, Electrical
Power and Energy Systems, Vol. 36, pp 13-17,
Computational Chemotaxis in Bacteria Foraging
Optimization; An analysis, IEEE Transaction on
14. J. Brownlee, Clever Algorithm; Nature Inspired
Programming Recipes, Amazon Publishers, June, 2012
15. K.M.Passino, Bacteria Foraging Optimization,
International Journal of Swarm Intelligence Research,
Vol. 1, No. 1, pp 1-16, January – March, 2010
16. C.Hanning, Z. Yunlong, H. Kunyuan, Adaptive Bacteria
Foraging Optimization Research Article, Abstract and
17. Jun Li, J. Dong, Feng Bu, J. Wang, Analysis and
Improvement of the Bacteria Foraging Optimization
Algorithm, Journal of Computing Science and Engineering
Vol. 8, No 1, pp 1-10, March, 2014.
18. M. Mam, G. Leena, N.S. Saxena, Distribution Network
Reconfiguration for Power Loss Minimization using
Bacteria Foraging Optimization Algorithm, IJ. Engineering

Figure 3. Generalized process flow chart for Framework on
Loss Minimization using Bacteria Foraging Optimization
Algorithm (BFOA).