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RURAL TRANSFORMATION: Optimization of Household wiring system by ant colony algorithm

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ABSTRACT
Electrical distribution networks are structurally weakly meshed, but are typically operated in radial configurations to simplify the network protection schemes. This implies the need to carry out suitable selection of the redundant network branches to open in normal conditions, as well as to define the control variables to set up to guarantee effective system operation and voltage quality. Furthermore, the structure of the distribution networks must be upgraded to meet future needs, according to economic objective functions defined for distribution system planning. Objective or sole moto of this team to build and develop something for the upliftment of the Rural sector of our country. We dream to transform rural sectors by providing an efficient solution for electricity distribution system. This will also reduce the burden and strain on the government.
People with low family income can afford a better household wiring. The wiring system that will be provided by us will take care of the number and types of the appliances used in the house and the design of the house. Successful implementation of our idea will not only the reduce the cost of wiring but will also reduce the wastage of energy and resources. So, we aim to provide the complete solution to problems that people of today's rural area are facing in their daily life due to poor wiring system.
We will also work upon to reduce the chances of short circuits and electricity leakages. For the better understanding of the real problems, we travelled through many rural areas. We analyzed the household wirings of some of the houses at random and tried our best to bring out the flaws in them. We also approached people to share their problems due to their inefficient household wiring.
In Optimization of Household wiring system, we are trying to build an algorithm that would minimize the cost of household wirings, by minimizing the length of wire. Lesser is length of wire lesser is the energy loss due to resistance and eddy current
By this project we aim to spread the awareness among people about benefits of having efficient wiring system. We are trying to educate them about the energy and resource losses that our country is facing today. This study proposes an optimization method for transformer sizing in power system using ant colony optimization and a verification of the process by MATLAB (matrix laboratory) software. The aim is to address the issue of transformer sizing which is a major challenge affecting its effective performance, longevity, huge capital cost and power loss. This method accounts for the constraints imposed by the load capacity and the thermal overload that the transformer serves throughout its lifetime. The objective function to be minimized includes the transformer capital cost as well as the energy loss cost. In this paper, the Optimal Transformer Sizing (OTS) problem which is fundamentally the basic routine for the location of transformer was addressed by means of the heuristic Ant System Method using the Elitist strategy, called Elitist Any System (EAS). EAS belong to the family of Ant Colony Optimization (ACO) algorithm. ACO when appropriately applied determines the least cost path, taking into consideration the various essential factors including transformer bid price, growth rate, inflation rate, peak load, thermal deviation, and energy loss cost. The study demonstrated a significant saving in capital cost using this approach as evidenced from the changes to the transformer following the initial installed capacity of 190kVA to 320kVA in the second stage and then finally to 630kVA in the third stage which effectively supported the remaining period under consideration. This finding contrasts with the traditional simplified sizing strategy usually adopted by utilities companies.
Keywords — Ant Colony Optimization, wire, cost

I. INTRODUCTION

Ant colony optimization (ACO) is a population-based metaheuristic that can be used to find approximate solutions to difficult optimization problems. In ACO, a set of software agents called artificial ants search for good solutions to a given optimization problem. To apply ACO, the optimization problem is transformed into the problem of finding the best path on a weighted graph. The artificial ants (hereafter ants) incrementally build solutions by moving on the graph. The solution construction process is stochastic and is biased by a pheromone model, that is, a set of parameters associated with graph components (either nodes or edges) whose values are modified at runtime by the ants.

Explaining ACO through an example

The easiest way to understand how ant colony optimization works is by means of an example. We consider its application to the traveling salesperson problem (TSP). In the TSP a set of locations (e.g., cities) and the distances between them are given. The problem consists of finding a closed tour of minimal length that visits each city once and only once.

To apply ACO to the TSP, we consider the graph defined by associating the set of cities with the set of vertices of the graph. This graph is called construction graph. Since in the TSP it is possible to move from any given city to any other city, the construction graph is fully connected and the number of vertices is equal to the number of cities. We set the lengths of the edges between the vertices to be proportional to the distances between the cities represented by these vertices and we associate pheromone values and heuristic values with the edges of the graph. Pheromone values are modified at runtime and represent the cumulated experience of the ant colony, while heuristic values are problem dependent values that, in the case of the TSP, are set to be the inverse of the lengths of the edges.

The ants construct the solutions as follows. Each ant starts from a randomly selected. Then, at each construction step it moves along the edges of the graph. Each ant keeps a memory of its path, and in subsequent steps it chooses among the edges that do not lead to vertices that it has already visited. An ant has constructed a solution once it has visited all the vertices of the graph. At each construction step, an ant probabilistically chooses the edge to follow among those that lead to yet unvisited vertices. The probabilistic rule is biased by pheromone values and heuristic information: the higher the pheromone and the heuristic value associated to an edge, the higher the probability an ant will choose that edge. Once all the ants have completed their tour, the pheromone on the edges is updated. Each of the pheromone values is initially decreased by a certain percentage. Each edge then receives an amount of additional pheromone proportional to the quality of the solutions to which it belongs (there is one solution per ant).

This procedure is repeatedly applied until a termination criterion is satisfied.

Ant colony system:

The first major improvement over the original ant system to be proposed was ant colony system (ACS), introduced by Dorigo and Gambardella (1997). The first significant difference between ACS and AS is the form of the decision rule used by the ants during the construction process. Ants in ACS use the so-called pseudorandom proportional rule: the probability for an ant to move from city i to city j depends on a random variable q uniformly distributed over [0,1], and a parameter q0; if q≤q0, then, among the feasible components, the component that maximizes the product τilηβil is chosen; otherwise, the same equation as in AS is used.

This greedy rule, which favours exploitation of the pheromone information, is counterbalanced by the introduction of a diversifying component: the local pheromone update. The local pheromone update is performed by all ants after each construction step. Each ant applies it only to the last edge traversed:

$$\tau ij=(1-\varphi)\cdot\tau ij+\varphi\cdot\tau 0,$$

where φ∈ (0,1] is the pheromone decay coefficient, and τ0 is the initial value of the pheromone.

The main goal of the local update is to diversify the search performed by subsequent ants during one iteration. In fact, decreasing the pheromone concentration on the edges as they are traversed during one iteration encourages subsequent ants to choose other edges and hence to produce different solutions. This makes less likely that several ants produce identical solutions during one iteration. Additionally, because of the local pheromone update in ACS, the minimum values of the pheromone are limited.

As in AS, also in ACS at the end of the construction process a pheromone update, called offline pheromone update, is performed.

ACS offline pheromone update is performed only by the best ant, that is, only edges that were visited by the best ant are updated, according to the equation:

$$\tau ij\leftarrow(1-\rho)\cdot\tau ij+\rho\cdot\Delta\tau bestij$$

where Δτbestij=1/Lbest if the best ant used edge (i,j) in its tour, Δτbestij=0 otherwise

(Lbest can be set to either the length of the best tour found in the current iteration -- iteration-best, Lib -- or the best solution found since the start of the algorithm -- best-so-far, Lbs).

It should be noted that most of the innovations introduced by ACS were introduced first in Ant-Q, a preliminary version of ACS by the same authors.

II. PROBLEM STATEMENT

Electricity must be distributed in many houses on a locality through wires and further the electricity is distributed in the house in at different points. We must find the path or the order in which the wiring should be done which uses minimum length of wire.

III. THE PRINCIPLE

- Initially, the ants are all concentrated in the colony, and they need to find the location of food and bring the food home. In the beginning, all ant moves randomly.
- As the ant moves, it will lay down pheromone trials. Pheromone is attractive to ant: when other ants find move to the position with pheromone, they will tend to move along the path instead of moving in a random pattern.
- The pheromone will evaporate overtime, thus reducing the attractiveness to the ant.
- After some time (some iterations), the path with better performance will be strengthened (since ants will follow the path more likely as well as lay down pheromone to strengthen the attraction, this is the positive feedback!), the path with deficient performance will disappear (less attractive to ant + pheromone evaporation)
- And eventually, the ants will find the optimal path

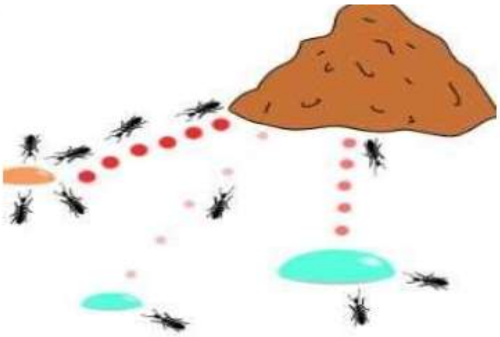

Fig 1. Ant colony

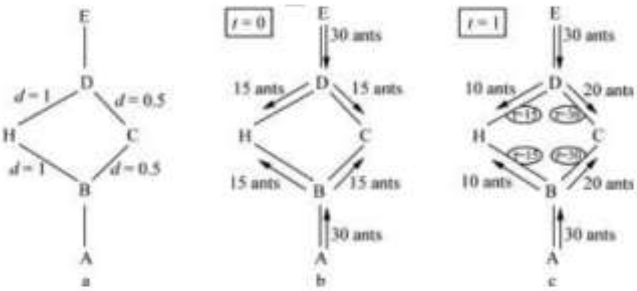

Fig 2. Ant's structure

IV. APPLICATIONS

The initial applications of ACO were in the domain of NP-hard combinatorial optimization problems. The largest body of ACO research is still, not surprisingly, to be found in this area. The interested reader will find a complete overview of these applications in (Dorigo & Stützle 2004). Another application that was considered early in the history of ACO is routing in telecommunication networks. A particularly successful example of ACO algorithm in this domain is AntNet (Di Caro & Dorigo 1998). Current research in ACO algorithms is devoted both to the development of theoretical foundations and to the application of the metaheuristic to new challenging problems. The development of theoretical foundation was started by Gutjahr, who was the first to prove convergence in probability of an ACO algorithm (Gutjahr 2000). An overview of theoretical results available for ACO can be found in (Dorigo & Blum 2005). Concerning applications, the use of ACO for the solution of dynamic, multiobjective, stochastic, continuous, and mixed-variable optimization problems is a current hot topic, as well as the creation of parallel implementations capable of taking advantage of the new available parallel hardware.

Ant colony optimization applications In the ACO application presented in Carpaneto & Chicco, 2005, the pheromone is associated to the individual planning actions. Initially, all planning actions $j \in J$ are associated to the same quantity of pheromone $\tau 0$. During the iterative process, each ant m = 1, M activates several planning actions chosen at random by applying the weighted probabilistic selection mechanism according to the probabilities (1), depending on the distance formulated for the specific problem. For instance, the application presented in Carpaneto & Chicco, 2005, deals with the placement of remote controllers in the distribution system nodes, considering as planning action the placement of an individual remote controller in a node belonging to a set of candidate nodes. In this case, the distance referring to a given node is the inverse of the product of the power not served times the equivalent failure rates in the upstream and downstream portions of the network with respect to that node. At the end of each iteration, the global heuristic rule is applied by evaporating part of the pheromone and increasing the pheromone quantity for the planning actions providing the best objective function during the iteration (if the solution is the best one found so far, the amplification factor is higher than the one used for the best solution at the current iteration). In Favuzza et al., 2006, and Favuzza et al., 2007, the problem is represented as a graph, in which the (reinforced) distribution system configurations at the different years are the nodes, and the distances between the nodes are the actualized transition costs (including investment and operation) from the reference configuration to the new one. In this application, the set of nodes to be visited is not unique, but it is in principle infinite. The solution algorithm is then set up as a dynamic ant colony search, in which the algorithm creates at each year a finite number of candidate solutions, forming a dynamic tree structure. A parameter Ns is introduced to set up the number of candidate solutions generated (corresponding for instance to varied sizes of the local generation units), and a mechanism to replace the worst search directions with most convenient ones (in terms of pheromone value and distance) is included to avoid excessive expansion of the dynamic tree during the solution process. Each resulting multi-year path is associated to a cost determined as the sum of the actualized transition costs. The selection is carried out by using elitistic considerations. The user-defined parameter q0 is adapted during the solution process, decreasing it when the number of successive solutions without improvement increases, thus reducing the importance of elitistic choice in favour of the weighted probabilistic selection. The pheromone is updated according to the standard local heuristic rule, and to the global heuristic rule (2) applied at the end of each iteration, in which the function ψh is the inverse of the cost of the best path found during the iteration. In Gomez et al. 2004, initially a random pheromone quantity is associated to each branch of the network. Then, each ant explores the network to reach all its nodes with a radial network, with a search guided by the weighted probabilistic selection mechanism illustrated. The selection is carried out by using elitistic considerations. Classical local and global heuristic rules are used for pheromone update. In the global heuristic rule (2), the function $\psi h = \kappa\ \tau/chmin$ is given by the ratio between the user-defined factor $\kappa\tau$ and the minimum cost of the best path found during the iteration. The distance used for pheromone update considers the branch length, the magnitude of the load at the end of the path, and the incremental cost of the network.

With the rate of population growth constantly increasing in Nigeria, the demand for electrical power will significantly increase to meet current demand. Therefore, if proper future analysis is not taken into consideration, the problem of epileptic power (cut in electricity) would persist and continue to be the order of the day. Thus, the major challenges facing the transformer and its life span include improper location of transformer, sizing and loading effect. An approach towards addressing these problems will involve proper optimisation by considering the initial loading condition of the transformer future expected load, temperature rise, the transformer's iron, and copper losses, etc.

Transformer sizing optimisation is a multi-objective function, and therefore the optimal choice of the transformer size cannot be directly achieved. The strategy adopted by the electric utility companies for transformer sizing is to install transformers which meet the current load demand for a specific location without allowance for the more demand in the future. Consequently, the future demand of required power from the existing installed transformer become insufficient in meeting the demand of the growing population. This approach used by utility companies in Nigeria seems obsolete with lots of uncertainty for the future. One method referred to as Deterministic Optimisation methods could offer solution to this problem by applying either dynamic programming [3] or integer programming. However, the wide spectrum of transformer sizes and various load types involved in the electric utility distribution system make the transformer sizing a challenging combinatorial optimisation problem, since the space of solutions is huge. That is why stochastic optimisation methods may prove to provide more robust solutions.

V. CONCLUSION

Ant Colony Optimization (ACO) algorithm was created considering the various objective functions using Elitist Ant System (EAS) approach for the optimization of the transformer sizing problem. Dorigo first proposed the EAS in his doctoral research and later in a peer reviewed publication. The ACO algorithm is inspired by the behavior of real ant colonies used to solve combinatorial optimization problem. The real ants lay down in some quantity an aromatic substance, known as pheromone, on their way to food source. The pheromone quantity depends on the length of the path and the quality of the discovered food source. An ant chooses an exact path in connection with the intensity of the pheromone. The pheromone trail evaporates over time if no more pheromone is laid down. Other ants are attracted to follow the pheromone trail. Therefore, the path will be marked again and it will attract more ants to use the same path. The pheromone trail on paths leading to rich food sources closest to the nest will be more visited and will therefore grow faster. In this way, the best solution has more intensive pheromone and higher probability to be chosen. In this study, an ant colony optimization technique was applied to transformer sizing problem (three phases, oil immersed, air-cooled transformers). The objective function to be minimized include transformer capital cost and energy loss cost. The calculation considers constraint such as insulation aging throughout the transformer life cycle for the specified period of installation. Although, there is extensive literature on transformer sizing problem, very few explained the dynamics of transformer sizing using MATLAB software to compute the optimization algorithm. As MATLAB software has the capability to handle extensive data and produce repeatable results of cumbersome analysis with much less cost, it was thought beneficial to simulate an optimization using the software to advance the EAS model. Elefterios, et al [8] proposed the MATLAB simulation that was based on the non –deterministic methodology.

VI. OUTPUT RESULTS

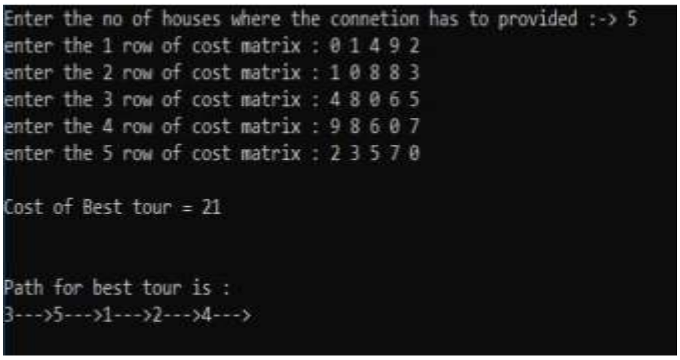

Fig 3. Output

	Ant colony optimisation	
Input size	Input Range	Time taken
5	Between 0 to 20	12.56
5	Between 20 to 40	13.15
5	Between 40 to 100	13.54
15	Between 0 to 20	16.47
15	Between 20 to 40	17.01
15	Between 40 to 100	17.45
50	Between 0 to 20	24.12
50	Between 20 to 40	25.56
50	Between 40 to 100	28.12
100	Between 0 to 20	37.45
100	Between 20 to 40	39.47
100	Between 40 to 100	42.14

Fig 4. Ant Colony Optimization

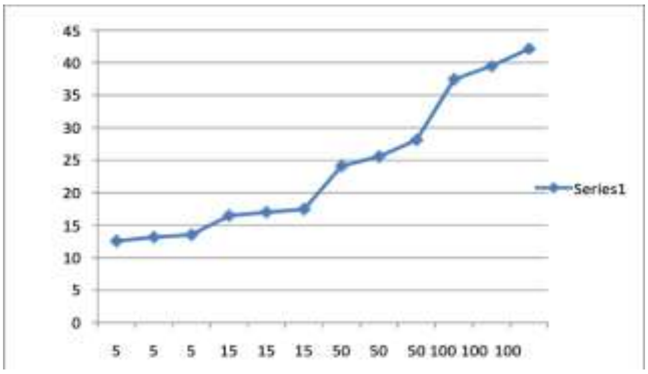

Fig 5. ACO Graph

	Brute force	
Input size	Input Range	Time taken
5	Between 0 to 20	14.56
5	Between 20 to 40	15.14
5	Between 40 to 100	16.47
15	Between 0 to 20	20.14
15	Between 20 to 40	21.14
15	Between 40 to 100	21.57
50	Between 0 to 20	45.14
50	Between 20 to 40	47.25
50	Between 40 to 100	50.06
100	Between 0 to 20	80.54
100	Between 20 to 40	82.04
100	Between 40 to 100	85.45

Fig 6. Brute Force

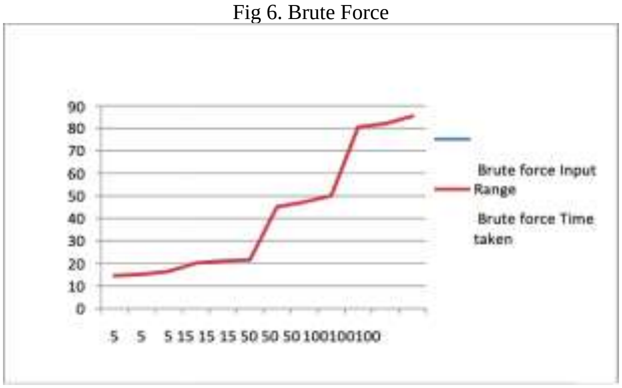

Fig 7. Brute Force Graph

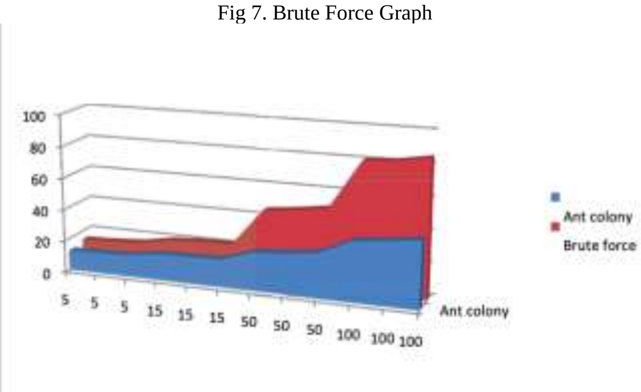

Fig 8. Comparison Between ACO and Brute Force

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REFERENCES

[1] Liu, C. (2019). Optimal design of high-rise building wiring based on ant colony optimization. Cluster Computing, 22(2), 3479-3486.

[2] Meziane, R., Massim, Y., Zeblah, A., Ghoraf, A., & Rahli, R. (2005). Reliability optimization using ant colony algorithm under performance and cost constraints. Electric power systems research, 76(1-3), 1-8.

[3] Toksari, M. D. (2016). A hybrid algorithm of Ant Colony Optimization (ACO) and Iterated Local Search (ILS) for estimating electricity domestic consumption: Case of Turkey. International Journal of Electrical Power & Energy Systems, 78, 776-782.

[4] Molla, T., Khan, B., & Singh, P. (2018). A comprehensive analysis of smart home energy management system optimization techniques. Journal of Autonomous Intelligence, 1(1), 15-21.

[5] R. E. Sorace, V. S. Reinhardt, and S. A. Vaughn, “High-speed digital-to-RF converter,” U.S. Patent 5 668 842, Sept. 16, 1997.

[6] Ant colony Optimization Algorithms, website: http://mat.uab.cat/~alseda/MasterOpt/ACO_Intro.pdf

[7] Silva, B. N., & Han, K. (2019). Mutation operator integrated ant colony optimization based domestic appliance scheduling for lucrative demand side management. Future generation computer systems, 100, 557-568.

[8] Wang, J., Cao, J., Li, B., Lee, S., & Sherratt, R. S. (2015). Bio-inspired ant colony optimization based clustering algorithm with mobile sinks for applications in consumer home automation networks. IEEE Transactions on Consumer Electronics, 61(4), 438-444.

[9] Galehdar, A., Thiel, D. V., Lewis, A., & Randall, M. (2009). Multiobjective optimization for small meander wire dipole antennas in a fixed area using ant colony system. International Journal of RF and Microwave Computer-Aided Engineering: Co-sponsored by the Center for Advanced Manufacturing and Packaging of Microwave, Optical, and Digital Electronics (CAMPmode) at the University of Colorado at Boulder, 19(5), 592-597.

[10] Ant colony Optimization, website: http://www.scholarpedia.org/article/Ant_colony_optimization