ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 4, Issue 11, May 2015

New Metaheuristic Methodology for Loss Reduction through Feeder Reconfiguration

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Abstract*— This paper presents a new metaheuristic methodology, for Feeder Reconfiguration in distribution networks, called Item Oriented Ant Colony Optimization (IOACO), with four variations based on different Ant Colony Optimization algorithm approaches (ACO). The methodology modifies and adapts previously proposed ACO methods in order to improve their efficiency and accuracy in solving the problem of loss reduction in a distribution network.

***Index Terms*—Feeder reconfiguration, Ant Colony Optimization, Metaheuristic Optimization Techniques.**

I. INTRODUCTION

Feeder Reconfiguration or Network Topology Reconfiguration consists on the topology modification of an Electrical System by closing or opening tie and sectionalizing switches, in order to obtain a better performance of the system. It has been used for loss reduction, load balancing, minimization of voltage drop, and minimization of service interruption, frequency network restoration and balanced service. Generally, distribution systems are built as weakly meshed networks. However, they are operated as radial networks. Finding the optimal tie switches to make the meshed networks radial is a highly complicated combinatorial optimization problem. There are three ways to approach feeder reconfiguration: Linear Programming, Heuristic Techniques and Metaheuristic Techniques. Linear Programming has been mainly used for planning applications. Focusing on Heuristic Techniques for feeder reconfiguration, the concept was first introduced by Merlin et al. [1]. Their paper proposed a "branch and bound" methodology: all network switches are initially closed, and a switch is to be opened at each stage and selected to minimize resistive line power losses of the resulting network. The methodology was improved by Shirmohammadi et al. who considered the loads to be voltage dependent current injections [2]. Following the branch and bound approach, Goswami et al. proposed an algorithm which optimizes the flow pattern in a single loop of the network [3]. Borozan et al. [4] used the methodology proposed by Merlin to be applied in real-time on real-sized networks. Civanlar et al. proposed a branch exchange methodology and a simplified but efficient formula for loss reduction [5]. In order to improve the methodology proposed by Civanlar et al., Baran and Wu [1][6] introduced a two approximation set of power flow equations for load balancing and loss reduction. Also based on Civanlar's proposal, Taleski et al. used a branch exchange method focusing on energy losses rather than in power losses, so that loads and voltages vary through time and plenty of input information is required [7]. Taylor et al used a best-first tree searching strategy, constructing a decision tree to represent the available switching operations [8]. Sarfi et al. introduced network partitioning theory by weighting the line sections of the distribution system according to associated power losses and partitioning them into blocks of busses [9]. More recently, metaheuristic techniques have been applied to the problem of feeder reconfiguration. Nara et al. [10] had already used Genetic Algorithms obtaining close to global optima solutions but with problems in terms of long codification leading to big computation times. Romero et al. also used GA adding a path to node approach. The paths linking buses and substations were defined and used to create the initial population of the GA [11]. More studies were made by [12-13]. Further metaheuristic techniques have been used, such as fuzzy logic by [14], Tabu Search alone [15-16] and combined with Simulate Annealing [17] have also been applied to the feeder reconfiguration problem. Among these metaheuristic optimization techniques, Ant Colony Optimization algorithms were proposed by Dorigo[18-21]. Further ACO algorithms have been proposed to improve the efficiency of the initial method, and adapt to different optimization problems [22-27]. Ant Colony Optimization algorithms have been successfully applied to minimize losses through feeder reconfiguration [28-31] and have even been considered for loss reduction and load balancing in networks including Distributed Generation [31]. Besides, hybrid algorithms, including ACO have been used to address the load balancing and the loss reduction problems. [32-34]. Recently, Hyper-cube Ant Colony algorithms have been applied to solve the loss reduction through feeder reconfiguration problem [35-36]. Multiobjective feeder reconfiguration can also be achieved using ACO [37]. This paper proposes four methodologies based on different ACO approaches adapted to the problem of feeder reconfiguration. The main goal to achieve is to find a better global optimal solution and improve efficiency and performance, minimizing power losses in large scale distribution systems with presence of Distributed Generation.

II. PROBLEM FORMULATION

The power losses are calculated on an n-node system of known topology. The location and characteristics of the demand, as well as the generation, are known and constant. The base for the calculation of power losses is the power flow. Thus, for a given network, the bus voltages and the active and reactive power flow along the branches are calculated. The

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
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power flow problem consists on solving the nonlinear equation problem expressed by Cartesian equations (1) and (2). Also, equation (3) describes the problem of calculating power losses [5][29-30].

$$P_i = Re\{V_i^* \cdot V_i \cdot Y_{ii} + V_i^* \sum_{j=1}^{n} Y_{ij} V_j\}(j \neq i) \quad (1)$$

$$Q_i = -Im\{V_i^* \cdot V_i \cdot Y_{ii} + V_i^* \sum_{j=1}^{n} Y_{ij} V_j\}(j \neq i) \quad (2)$$

Where:

$\mathbf{P_i}$	real power balance in bus *i*
$\mathbf{Q_i}$	reactive power balance in bus *i*
$\mathbf{V_i}$	complex voltage of node *i*
$\mathbf{V_j}$	complex voltage of node *j*
$\mathbf{Y_{ii}}$, $\mathbf{Y_{ij}}$	admittance matrix components of the system bus

$$P_{losses} = Re\{V_i \cdot I_{ij}^* + V_j \cdot I_{ji}^*\} \quad (3)$$

Where, currents Iij and Iji are determined by equations (4) and (5)[5].

$$I_{ij} = y_{ij} \cdot (V_i - V_j) + y_{i0} \cdot V_i \quad (4)$$

$$I_{ji} = y_{ij} \cdot (V_j - V_i) + y_{i0} \cdot V_j \quad (5)$$

Once losses are calculated, changes in losses can be calculated as a result of a load transfer between feeders [5-6]. The optimization problem is subjected to network stability constraints. For secure operation, the bus voltage must be maintained within its limits, as in equation (6)[29]. The limits are established in the European Standard EN50160 as well as in the IEEE C84.1 Standard.

$$V_{min} \leq |V_i| \leq V_{max} \quad (6)$$

Also, the current must not exceed the thermal rating of the feeder, as seen in equation (7)[29].

$$|I_i| \leq I_{i,max} \quad (7)$$

On the other hand, the distribution network cannot present any islands. To comply with these constraints, penalization factors are used. Thus, the objective function can be formulated as the minimization of the power losses, to which penalizations are added. The objective function is described in equation (8)[5][29-30].

$$minF = \min(P_{losses} + \lambda_v C_v + \lambda_i i C_i + \lambda_{LM} C_{LM}) \quad (8)$$

Where:

$\mathbf{P_{losses}}$	system power losses
$\boldsymbol{\lambda_V}$	voltage constraint penalization constant
$\mathbf{C_V}$	squared number of voltage violations
$\boldsymbol{\lambda_i}$	current constraint penalization constant
$\mathbf{C_i}$	squared number of current violations
$\boldsymbol{\lambda_{LM}}$	loss of mains constraint penalization constant
$\mathbf{C_{LM}}$	squared number of islands in the system

III. NEW METHODOLOGY

Ant Colony Optimization algorithms are constituted by a set of artificial ant individuals that cooperate and exchange information. Each artificial ant finds its own artificial path and modifies it by depositing pheromone on it, in order to solve an optimization problem [18]. The optimization problem in this case is the feeder reconfiguration of the distribution network. A normally open switch (tie switch) and a set of normally closed switches (sectionalizing switches) linking one substation to another form a loop. To make the distribution network radial, a tie switch has to be selected in each loop. The appropriate tie switch combination minimizes the power losses. Loops gathering groups of remote controlled switches of the feeders between substations form the Search Space. This is the space of combinatorial possibilities where the artificial ants will carry their search. Each loop is composed by the switches that form the vertices of the Search Space. Thus, the loops consist on a succession of switches, each of them identified by a number or code. When a valid Search Space has been created by the previous procedure, the Ant Colony optimization algorithms can be applied over that Search Space. Four methodologies based on Ant Colony Optimization theory have been proposed in this paper. Unlike in previous feeder reconfiguration methodologies using ACO [28-31], the four methodologies proposed in this paper do not consider the feeder reconfiguration problem as an ordering problem. Thus, the pheromone and the function fitness are associated directly to the items, not to the path among items. This is a characteristic of subset problems [22-23]. However, the way the problem is posed in this new methodology, it is neither an ordering problem, nor a subset problem. In subset problems each solution can have a different amount of items, whilst in ordering problems, the order affects the fitness. In the new methodology proposed (Item Oriented Ant Colony Optimization-IOACO), the number of items that form the solution is fixed. Also, at least one item from each loop has to be selected. However, it is not specifically an ordering problem, because the information can be attached to each item and not to the path between items. It is the choice of the item itself that defines the solution fitness and not the path followed to construct this solution. For the network reconfiguration problem, the items forming the Search Space are the switches of the distribution network. Once the objective function is determined, the IOACO is applied in order to achieve the optimization goal. The Search Space is composed by ‘n’ loops formed by the system switches. In each loop, a switch has to be chosen in order to form a valid network topology configuration. Namely, each artificial ant has to choose ‘n’ switches by the end of the search. The solution length is fixed, so each artificial ant needs the same time to complete a solution. The generic process can be described as follows:

- First, the power losses and constraints of the original network configuration are calculated. Thus, it is possible to establish the fitness of this original configuration.
- Secondly, all elements/vertices of the Search Space are given an initial amount of pheromone, τ_0.
- Then, a number of ‘m’ artificial ants (hereafter called ants) are randomly placed throughout the Search Space.

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 4, Issue 11, May 2015

- Afterwards, each ant begins a parallel search for the solution. They incorporate new elements to the solution by applying the state transition rule.
- All ants finish building their solutions at the same time. Then, pheromone of all elements forming the Search Space is updated according to the global updating rule.
- The ant that has performed best from the beginning of the algorithm is kept for comparison with future iterations.
- This process is repeated until termination conditions are met: a) the maximum iteration number 'n' is reached, b) all ants have selected the same tour.

The development of the process can be done in a distribution network with or without presence of Distributed Generation.

Depending on the ACO theory basis used to develop the algorithm four methodologies are proposed in this paper.

A. Item Oriented Ant System (IOAS)

This first approach follows the basic steps defined on the previous section. It is based in the Ant System (AS) methodology [18][20]. The steps taken for its implementation can be resumed as follows:

- First, the loop from which the ant has to select an element has to be found. This is done by rotating the loops.
- Then, the power losses and penalizations are calculated in order to set the fitness (η) of each element of the loop.
- Then the random proportional rule is applied to determine the probability with which each element might be chosen. The random proportional rule takes into account the exploitation information (pheromone) and the heuristic associated to the item (fitness), which adds an explorative characteristic to the search.
- After all ants have completed their tours, the best ant of the iteration is chosen and compared to the global best ant: the ant that has provided the best solution since the beginning of the iterations. The best of both is chosen.
- After this process, pheromone evaporates from all Search Space elements proportionally to the pheromone evaporation rate (1-δ).
- The elements belonging to the best global solution get pheromone reinforcement.

The state transition rule used by the new algorithm proposed calculates the probability with which a new element 'i' is added to the solution. The element must be selected from the ones belonging to a certain loop. Then, in the next step, the loop position rotates until each ant has selected 'n' elements. This state transition rule is based in the implementation of the random proportional rule given by equation (9) [18-22].

$$P_i = \begin{cases} \frac{[\tau(t)]^{\alpha}[\eta(k,t)]^{\beta}}{\sum_{j\in loop}[\tau(t)]^{\alpha}[\eta(k,t)]^{\beta}} & \text{if } j\in\text{loop} \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

Where:

k	ant *k*
t	step that ant *k* takes
τ	pheromone deposited in a certain item
η	fitness, pseudo-utility, the local heuristic associated to the item
α	weighting factor for the pheromone
β	weighting factor for the heuristic
allowed$_k$	set of items still not considered by the *k*th ant
i,j	items of the loop

The proposed methodology calculates the new pheromone levels of the items (i.e., switches composing the Search Space) using equations (10) and (11).

$$\tau_i = (1-\delta)\tau_i + \delta\Delta\tau_i \tag{10}$$

$$\Delta\tau_i = \frac{Q}{\eta_{best}} \tag{11}$$

Where:

τ_i	pheromone accumulated in item *i*
Δτ	pheromone variation
δ	pheromone evaporation factor for the "global updating rule"
(1- δ)	pheromone evaporation rate for the "global updating rule"
Q	constant that depends on case features
η_{best}	fitness of the best global ant

The pheromone reinforcement is proportional to the pheromone variation, Δτ. This is directly proportional to a constant Q, which is empirically calculated and inversely proportional to the solution fitness. Q can have different values, normally within the interval (1, 10), and it depends on the network characteristics, the power losses value in the network and the levels of pheromone accumulation that want to be obtained.

B. Item Oriented Ant Colony System (IOACS)

This methodology is based in the Ant Colony System algorithm [19-20], which was developed to improve the performance and efficiency of the AS. As in ACS, it includes two variations that may improve significantly the performance of the new proposed algorithm. The first variation is the implementation of the state transition rule after the pseudo-random proportional rule. This pseudo-random proportional rule is given by equation (12)[18-21]. It uses a random variable that is produced between the uniformly distributed interval (0, 1) and compared to a threshold q_0, also chosen from the same interval. The threshold q_0 determines the relative importance of exploitation versus exploration. Its value is chosen according on the importance that the exploitation wants to be given versus the exploration. q_0 values higher than 0.5 account for higher exploitation while lower than 0.5 favor biased exploration. If q_0 equals 0.5, then exploration and exploitation have the same importance.

$$P_i = \begin{cases} \operatorname{argmax}\{[\tau(t)]^{\alpha}[\eta(k,t)]^{\beta}\} & \text{if } q\le q_0 \\ \frac{[\tau(t)]^{\alpha}[\eta(k,t)]^{\beta}}{\sum_{j\in loop}[\tau(t)]^{\alpha}[\eta(k,t)]^{\beta}} & \text{otherwise} \end{cases} \tag{12}$$

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 4, Issue 11, May 2015

Where:

Q	random number uniformly distributed in [0,....,1]
q_0	parameter $0\leq q0\leq 1$
τ	pheromone accumulated in a certain item
η	fitness of solution if item k is chosen
α	weighting factor for exploitation
β	weighting factor for exploration

The second variation is the inclusion of a local pheromone updating rule. After each ant adds a new element for the solution, its fitness is calculated. When a new ant adds an item, it is compared with the solution of the previous one and the best of both is stored while the other is discarded. The pheromone is updated not after all ants have completed their solutions, but after every time all ants incorporate a new item to each solution. The pheromone update is done only for the element that the best ant has chosen. Pheromone evaporates from the rest of items. The update is done following equation (13).

$$\tau_i = (1-\rho)\tau + \rho\tau_0 \qquad (13)$$

Where:

τ_i	pheromone accumulated in item i
τ_0	pheromone initialization value
ρ	pheromone evaporation factor for the "local updating rule"

The use of the local updating rule directs the search and avoids stagnation and results leading to local suboptimal solutions, whereas the pseudo-random proportional rule balances exploration vs. exploitation.

C. Item Oriented Max-min Ant System (IOMMAS)

IOMMAS includes two boundary conditions to keep pheromone within certain ranges, in order to avoid that excessive pheromone accumulation in some elements leads to stagnation and guarantee the explorative behavior of the algorithm. It is based in the Max-min Ant System proposed by [26-27]. Once the pheromone update of an element is applied, a checking is done to see if it is within the Max-min range. If the pheromone surpasses the maximum value, the value τ_{max} is assigned to the element, and if it is lower, a value of τ_{min} is assigned. The aim is the same as in IOACS, however, the proceeding is computationally more efficient as the process is simpler and requires fewer calculations.

D. Item Oriented Max-min Ant Colony System (IOMMACS)

The last variation is a hybrid approach that uses the normal IOACS but includes pheromone boundaries. Hence, not only the global updating rule is subjected to pheromone thresholds, but also the local updating rule. The process is similar: after assigning the pheromone, a control is done to check if it is within limits, if not, τ_{max} or τ_{min} values are applied depending on if it exceeds the maximum or does not reach the minimum.

IV. RESULTS

The four proposed techniques have been tested in two distribution networks, which are well documented in previous bibliography [5][29][31].

Both networks have been modeled using PSS/E 30.3.2 and a software tool has been developed and implemented in Python 2.3 for each of the four techniques.

The first network is a simple three feeder system. It is useful to validate the methodology and to parameterize the algorithm. The second network corresponds to a real distribution network. Thus, the new techniques can be tested in a more proving environment. Two scenarios are taken into account for this second network, with and without presence of Distributed Generation.

A. Three Feeder System

The distribution network is a simple three feeder system of 11.4kV, as can be seen on Fig.1. Further network data can be found in [29-31]. It is a meshed network which is operated as a radial network. Besides, it has sixteen switches, three of which have to remain open (three tie switches) in order to make radial operation possible. The total load power consumption amounts 28.7MW and 17.3MVAr and the installed capacitor banks provide 11.4MVAr. This distribution network has been modeled in PSS/E 30.3.2 according to the data presented in [29]. The losses calculated for this model's original configuration are 0.5114MW. The original configuration is formed by tie switches 15, 26 and 21. The first step has been to adjust the parameters of all four techniques. To serve this purpose, a set of parameterization tests have been done. The parameters that have obtained better results are shown in Table I. Regarding penalization factors, voltage, thermal limit and islanding operation violation have been given the same importance. The ratio of the weighting factors is determinant. It has been concluded that emphasizing the exploration factor improves the results considerably. Also, initial, maximum and minimum pheromone levels have been adjusted depending on the objective function values. These parameters have been obtained empirically by careful analysis of the solution construction and pheromone accumulation in the switches. The parameterization is valid for both networks. However the population and cycle sizes vary depending on the size of the distribution network. For the three feeder system, a population of three ants and a number of 30 cycles has been estimated as optimal. All four methodologies have been tried in the network and all of them have been able to find the optimal solution (Table II).

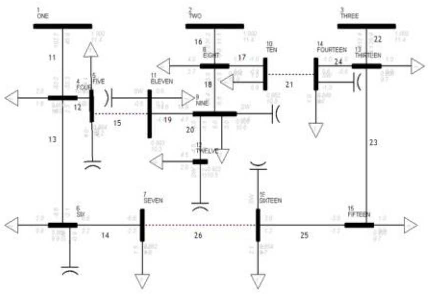

Fig.1. Three feeder system, single-line schematic

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 4, Issue 11, May 2015

TABLE I
PARAMETERS FOR IOACO

λ_V	λ_i	$\lambda_{islanding}$	α	β	δ
0.05	0.05	0.05	1	5	0.02

τ_0	q_0	Q	ρ	τ_{min}	τ_{max}
0.5	0.5	1	0.01	0.3	1

TABLE II
RESULTS FOR THE THREE FEEDER SYSTEMS

Method	Solution configuration	Losses (MW)	(%)
Su-ACS[29]	19, 17, 26	0.4682	8.8
IOAS	19, 17, 26	0.4682	8.8
IOMMAS	19, 17, 26	0.4682	8.8
IOACS	19, 17, 26	0.4682	8.8
IOMMACS	19, 17, 26	0.4682	8.8

These results are used as a first validation for the four techniques. They serve the purpose to minimize losses through feeder reconfiguration. However, the four techniques have to be tested in a bigger system in order to prove their real accuracy and efficiency.

B. Real distribution system without Distributed Generation

In this case, a 11.4kV real distribution network of Taiwan Power Company has been used for simulation purposes (Fig.2). Detailed network data can be found in [29-31].

It is provided by 2 main substations that supply 11 feeders, 83 sectionalizing switches (normally closed) and 13 tie switches (normally open). Three phase balance and constant load is assumed. The total active and reactive power for the whole system loads are 28.35 MW and 20.7 MVAr, respectively. According to both references [29-30], no capacitor banks are placed on this network. This distribution network has been modeled in PSS/E 30.3.2 according to the data presented in [29]. The losses calculated for the model's original configuration in PSS/E are 0.710855MW and the original configuration is formed by tie switches 84, 85, 86, 87, 88, 89, 90,91, 92, 93, 94, 95 and 96. Feeders on the left side of Fig. 2 (numbers 1, 12, 17, 28, 34, 48) are fed from substation 1 and feeders on the right side (numbers 53, 63, 73, 82, 87) are fed from substation 2. The network is operated radially. For this purpose, 13 switches must be opened on the right loops in order to guarantee the proper radial operation. Table III shows the results of the tests performed in this network. It compares the results obtained by all four IOACO techniques with previously used metaheuristics, more specifically Genetic Algorithms (GA), Ant System (AS) and Ant Colony System (ACS). The losses for GA, AS and ACS have been calculated for the PSS/E model for the solution configurations obtained in [29-31]. The best solution (global optima) is achieved by the the IOAS and IOACS techniques proposed in this paper as well as the ACS from [29] and [31]. All four methodologies achieve a power loss reduction of 12.21%, i.e., from the initial value of 0.710855MW to 0.624029MW.

TABLE III RESULTS FOR THE TPC SYSTEM WITHOUT DISTRIBUTED GENERATION

Method	Solution configuration	Losses (MW)	Reduct. (%)
Su-ACS [29]	55,7,86,72,13,89,90,8 392,39,34,41,62	0.624029	12.21
Wu-AS [31]	54,7,86,71,13,89,90,9 192,39,33,95,61	0.693989	2.37
Wu-ACS [31]	55,7,86,72,13,89,90,8 392,39,34,41,62	0.624029	12.21
Wu-GA [31]	55,7,86,72,88,89,90,8 392,93,33,95,61	0.625913	11.94
IOAS	55,7,86,72,13,89,90,8 392,39,34,41,62	0.624029	12.21
IOMMAS	55,7,86,72,88,89,90,8 392,37,33,40,62	0.633367	10.9
IOACS	55,7,86,72,13,89,90,8 392,39,34,41,62	0.624029	12.21
IOMMACS	84,7,86,72,76,14,90,8 392,29,34,40,64	0.642883	9.56

The genetic algorithm (GA) used by [31] achieves the next best solution, with power losses of 0.625913MW (11.94%).. The IOMMAS comes next with 10.9% reduction, also a very good solution, however further from the optimal, whereas IOMMACS is the one showing the worst results.

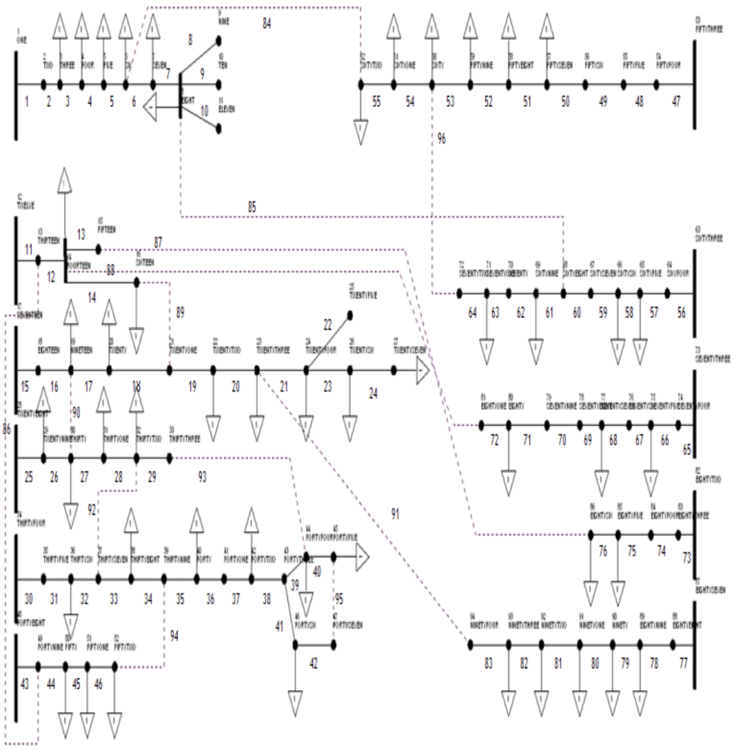

Fig.2. Taiwan Power Company distribution network, single-line diagram

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 4, Issue 11, May 2015

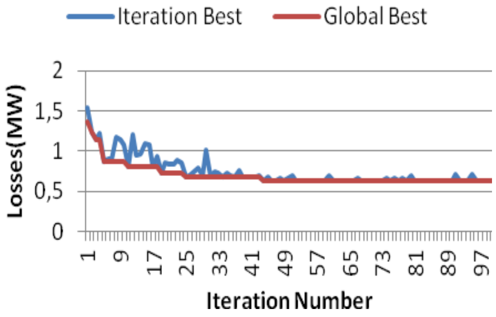

Fig.3. IOACS solution construction

Although its performance is worse than the other three methods, it is still a good solution, reducing the power losses in 9.56%, to 0.642883MW. The worst solution is the obtained by [31] with the AS, which only presents an improvement of 2.4%. Especially remarkable is the results obtained by the new Item Oriented Ant System (12.21% reduction) compared to the AS (2.4% reduction). Thus, the efficiency of the new methodology is confirmed. The IOACS is able to find the best solution, as does the ACS. Fig.3 shows an optimal solution construction for IOACS. It can be appreciated that it reaches convergence by iteration 52, so that it outperforms [29-31].

C. Real distribution system with Distributed Generation

The proposed IOACO methodology has been tested in the same distribution network, this time including Distributed Generation (DG). The DG units and their capacity are shown in Table IV. The rest of the network characteristics remain the same. The first aspect that has to be analyzed is the influence that the DG has in the initial configuration losses. A small penetration of well located DG units tends to reduce power losses, as can be seen on Table V.

TABLE IV INSTALLED DG

Bus	P(MW)	Q(MVAr)
8	0.25	0.1875
14	0.45	0.217944947
22	0.5	0.375
32	0.4	0.193728842
39	0.5	0.309872169
80	0.5	0
85	0.4	0.247897735
90	0.4	0.193728842

TABLE V
INITIAL CONFIGURATION LOSSES

	without DG	with DG
Initial configuration Losses (MW)	0.710855	0.5685

Thus, it is clear that the introduction of DG has a positive impact on power loss reduction. The implementation of IOACO results on a higher loss reduction. Table VI shows the results obtained by the four IOACO techniques and compares them to those obtained applying GA, AS, and ACS. The losses for GA, AS and ACS have been calculated in the PSS/E model for the solution configurations obtained in [29-31]. In this case, the best solution is obtained by the IOACS, with 10.83% of power loss reduction, showing that the methodology proposed in this paper is not only successful but obtains better results than previous methodologies. The GA by [31] is the second best. IOAS gives a much better result than AS and a better one than ACS. The methodologies achieving the worst results are AS and IOMMACS.

TABLE VI
INITIAL CONFIGURATION LOSSES

Method.	Solution configuration	Losses (MW)	Reduc (%)
Wu –AS [31]	55,6,86,72,13,89,90, 91,92,93,34,95,61	0.55038	1.35
Wu –ACS [31]	55,7,86,72,13,89,90, 83,92,39,34,41,62	0.535916	5.7
Wu –GA [31]	55,7,86,72,88,89,90, 83, 92,93,33,95,61	0.508852	10.49
IOAS	84,7,43,72,88,14,16, 91,92,39,46,40,62	0.53653	5.6
IOMMAS	84,7,86,66,75,14,90, 83,28,35,32,95,64	0.54221	4.62
IOACS	55,7,86,72,88,89,90, 83,92,39,33,40,63	0.50689	10.83
IOMMACS	54,59,43,71,74,89,9 0,81,25,29,34,41,62	0.56203	1.1

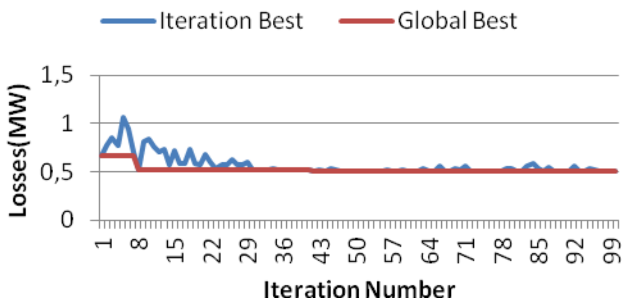

Fig.4. IOACS solution construction in Taiwan Power Company distribution system with DG

Fig.4 shows an optimal solution construction for IOACS. It can be appreciated that, once again, it reaches convergence around iteration 50, so that it outperforms [31].

The results obtained in this scenario confirm the success of IOACS and IOAS in being capable of offering better solutions than the existing methods, especially in networks with DG.

V. CONCLUSIONS

A new metaheuristic methodology based on ACO algorithms for feeder reconfiguration, with the purpose of loss minimization, has been proposed. This methodology has been called Item Oriented Ant Colony Optimization (IOACO). The new methodology does not approach the feeder reconfiguration problem as an ordering problem, but as a fixed length subset problem. Thus, the pheromone and the heuristic information are associated to the item. Four variations based on different ACO theories are proposed and tested in distribution networks with and without Distributed Generation. One of the proposed methodologies, IOACS proves to be more effective than other metaheuristic techniques applied to the same problem, especially for networks with DG. IOAS proves to be more efficient than its traditional analog AS. The other two, IOMMAS and IOMMACS, do not offer significant improvement compared to other existing met heuristics. To further enhance the presented work and once we have established the advantages of IOACS versus other met heuristics in the feeder topology reconfiguration problem, the new methodology should be tested in different networks presenting diverse Distributed Generation penetration and network stability problems in order to evaluate its ability to solve difficult situations caused by an increased penetration of Distributed Generation. Beyond the loss reduction problem, IOACS could also be tested for other optimization problems, such as load balancing or optimal capacitor placement.

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