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An Algorithmic Approach with Bee Colony Optimization to Load Profile Clustering

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Abstract:--This paper attempts to illustrate the potential of load profililing techniques to address the issue in automated meter reading and advanced metering infrastructure prevailing in electrical networks among present electricity markets. Though there are intelligent metering solutions are in the current market. This study has developed and tested an approach in accessing the consumers who do not possess digital meters by integrating ABC algorithm in load profile clustering. Results indicate that this approach is significantly stable and effective in accessing such consumers. Furthermore , the proposed algorithm is more effective and uncomplicated for the reason with few manipulations it can be operated to get desired output. Thus confirming to be an enhanced approach in relation with other existing approaches.

Keywords: Load profiling, artificial bee Colony algorithm, clustering techniques.

1. INTRODUCTION:

The present scenario of electricity market is flowing with a range of intelligent marketing solutions like AMR or AMI systems in order to address the challenges prevailing in metering technologies in general and in particular a customer without digital technology.In pursuit of this issue, LPing techniques are widely adopted to facilitate customers access the retail market and for tariff development purposes. Perhaps this technology categories customer based

on the shape of the year load profiles (LPS) and generates typical load profiles that can be used to formulate model load from distribution system. In this customer without digital meter is assigned a consumer category so as to get a unique profile and behavior as an outcome of the specified TLP to the corresponding category. A broad range of methods have been proposed and tested on different load profile databases , such as K-means or hierarchical clustering, self-organizing maps, neural networks , fuzzy systems , statistical methods or more recently, the Support Vector Clustering approach[1,2,3,4,5] This study proposes a new approach to the LP clustering by applying ABC algorithm . Furthermore due to the robustness and originality of this method. There are significant benefits like product quality of the results with effortless minor change on certain simple parameters. Indeed, it has greater efficiency than alternative clustering approaches. This paper highlights briefly the overview of the most popular clustering techniques [678]. Although data clustering aims to find structures in heterogeneous collection of data, these structure describe groups of data which a similar inside a group and dissimilar between different groups. The end result of the clustering algorithm or methodology depends mostly on the classification criterion and to separate similar and dissimilar data.

2. LOAD PROFILE CLUSTERING (LPC):

Clustering data aims to capture the structure in heterogeneous group of datas. These hierarchy defines collections (or)clusters of data which are unambiguous inside a group and ambiguous between different groups. The end solution of a clustering algorithm or hierarchy depends in great extend on the classification used to partition unambiguous and ambiguous datas. Clustering algorithms are applied in different kinds of applications such as web optimization, finance, biology, image processing etc. The clustering problem is defined in this paper consider the load description based on electric distribution network. One of the consumer model is Typical Load Profile(TLP).

A TLP explain the hourly values of electricity consumption on a daily basis and associated to consumer category. TLPs can be outlined for residential, commercial and industrial for seasonal factors. It can be developed for seasonal factors. It can be developed for climatic conditions that likely to happens in future using regressed technique. The widly used approached to structured TLP consist in gathering actual LP for various consumer categories , metered in network supply points and processing them using clustering algorithm to build TLPs. In order to setup a TLP portfolio any public utility must define a set of TLP that can be accurately possible load characteristics for all consumers in its self network. The maximum TLP and wider consumers include the portfolio and good representation of consumers in terms of accuracy.

3. ARTIFICIAL BEE COLONY ALGORITHM:

There are so many kind of swarms in the world. It is not possible to call all of them intelligentor their intelligence level could be vary from swarm to swarm. Self-organization is a key feature of a swarm system which results collective behaviour by means of local interactions among simple agents (Bonabeau et al. 1999). Bonabeau et al. (1999) interpreted the self-organization in swarms through four characteristics:

(i) *Positive feedback*: promoting the creation of convenient structures. Recruitment and reinforcement such as trail laying and following in some ant species can be shown as example of positive feedback.

(ii) *Negative feedback*: counterbalancing positive feedback and helping to stabilize the collective pattern. In order to avoid the saturation which might occur in terms of available foragers a negative feedback mechanism is needed.

(iii) *Fluctuations*: random walks, errors, random task switching among swarm individuals which are vital for creativity. Randomness is often significant for emergent structuressince it enables the discovery of new solutions.

(iv) *Multiple interactions*: agents in the swarm use the information coming from the other agents so that the information spreads throughout the network.

Additional to these characteristics, performing tasks simultaneously by specialized agents, called division of labour, is also an important feature of a swarm as well as self-organization for the occurrence of the intelligence (Bonabeau et al. 1997). According to Millonas, in order to call a swarm intelligent, the swarm must satisfy the following principles (Millonas 1994):

- The swarm should be able to do simple space and time computations (the proximity principle).
- The swarm should be able to respond to quality factors in the environment (the quality principle).
- The swarm should not commit its activities along excessively narrow channels (the principle of diverse response).
- The swarm should not change its mode of behaviour upon every fluctuation of theenvironment (the stability principle).
- The swarm must be able to change behaviour mode when needed (the adaptability principle).

4. STRUCTURE OF ABC:

As in the minimal model of forage selection of real honey bees, the colony of artificial bees in ABC contains three groups of bees: *employed bees* associated with specific food sources, *onlooker bees* watching the dance of employed bees within the hive to choose a food source, and *scout bees* searching for food sources randomly. Both onlookers and scouts are also called unemployed bees. Initially, all food source positions are discovered by scout bees.Thereafter, the nectar of food sources are exploited by employed bees and onlooker bees, and this continual exploitation will ultimately cause them to become exhausted. Then, the employed bee which was exploiting the exhausted food source becomes a scout bee in search of further food sources once again. In other words, the mployed bee whose food source has been exhausted becomes a scout bee. In ABC, the position of a food source represents a possible solution to the problem and the nectar amount of a food source corresponds to the quality (fitness) of the associated solution. In the basic form, the number of employed bees is equal to the number of food sources (solutions) since each employed bee is associated with one and only one food source.

In the initialization phase, the population of food sources (solutions) is initialized by artificial scout bees and control parameters are set. In the employed bees phase, artificial employed bees search for new food sources having more nectar within the neighbourhood of the food source in their memory. They find a neighbour food source and then evaluate its fitness. After producing the new food source, its fitness is calculated and a greedy selection is applied between it and its parent. After that, employed bees share their food source information with onlooker bees waiting in the hive by dancing on the dancing area. In the onlooker bees phase, artificial onlooker bees probabilistically choose their food sources depending on the information provided by the employed bees. For this purpose, a fitness based selection technique can be used, such as the roulette wheel selection method. After a food source for an onlooker bee is probabilistically chosen, a neighbourhood source is determined, and its fitness value is computed. As in the employed bees phase, a greedy selection is applied between two sources. In the scout bees phase, employed bees whose solutions cannot be improved through a predetermined number of trials, called "limit", become scouts and their solutions are abandoned. Then, the scouts start to search for new solutions, randomly. Hence, those sources which are initially poor or have been made poor by exploitation are abandoned and negativefeedback behaviour arises to balance the positive feedback. These three steps are repeated until a termination criteria is satisfied, for example a maximum cycle number or a maximum CPU time.

Detailed pseudo-code of the ABC algorithm seven steps are mentioned below:

Step1: *Initialize the population of solutions* x_{ij} *(i=1,2,…SN, j=1,2,…D). Evaluate the population, and cycle=1.*
Step2: *Repeat*
Step3: *Produce new solutions* v_{ij} *for the employed bees by using (2) and evaluate them, then apply the greedy selection process.*
Step4: *Calculate the probability values* p_i *for the solutions* x_i *by (1).*
Step5: *Produce the new solutions* v_{ij} *for the onlookers from the solutions* x_{ij} *selected depending on* p_i *and evaluate them, then apply the greedy selection process.*
Step6: *Determine the abandoned solution for the scout, if exists, and replace it with a new randomly produced solution* x_{ij} *by (3). And memorize the best solution achieved so far.*
Step7: *cycle = cycle + 1, until cycle = MCN.*
The Basic Algorithm of the ABC Process

5. ABC ALGORITHM TO LOAD PROFILE CLUSTERING :

5.1 Method of the study:

The implementation of the ABC algorithm to the LP clustering problem demands some adaptation and specification for the ABC algorithm described in section III.These aspects will be discussed forward.

For a general portfolio of NT typical load profiles, generated based on a set of NP metered LPs, the following metrics and performance indices have been considered:

Average distance between metered LPs and the associated TLP for consumer category t:

$$\sigma_t = \frac{1}{NP_t \cdot NH} \cdot \sum_{i=1}^{NP} \left\| LP_i - TLP_t \right\| \quad Class(i) \equiv t \quad t=1,\ldots,NT \quad (5)$$

Distance between TLPs s and t:

$$\rho_{s,t} = \frac{1}{NH} \cdot \left\| TLP_s - TLP_t \right\| \qquad s,t=1,\ldots,NT \qquad (7)$$

The above definitions use the following notations:

NT – number of clusters or TLPs; NPt – number of metered LPs for category or class t;

NP – total number of metered LPs; NH –number of values in a LP (NH=24 hours),

and Class (i) =t means that metered load profile i is from class t.

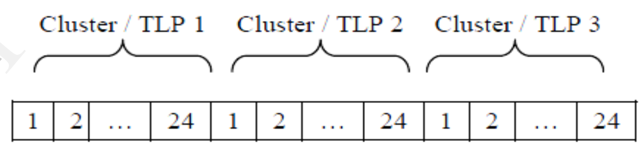

Fig.1. LP clustering problem with 3 TLPs.

6.2 Fitness Functions

The implementation of the ABC algorithm to the of LP clustering problem was studied for two distance metrics used as fitness function: F1 - fitness function based on the total average distance between metered LPs and the TLPs from equation (6) and F2 - fitness function based on the average distance between TLPs from (9) and the total average distance between metered LPs and TLPs from (6):

$$F_1 = 1/\sigma = 1/\left(\sum_{t=1}^{NT} \sigma_t / NT\right) \qquad (10)$$

$$F_2 = R - \sigma = \frac{1}{N_T} \cdot \sum_{s=1}^{NT} r_s - \frac{1}{N_T} \cdot \sum_{t=1}^{NT} \sigma_t \qquad (11)$$

Since the objective function of the ABC algorithm is always maximized, the fitness function F1 is defined as the inverse of the average distance σ. The metric from (4) takes simultaneously into consideration two types of distances: the distance between metered LPs and the associated TLPs (to be minimized) and the distances between TLPs (to be maximized). This way, metric (4) properly addresses the optimization approach meant to determine the best compromise between the number of TLPs and the accuracy of consumer representation. The implementation of the ABC algorithm to the LP clustering problem uses both type of fitness functions from (3) and (4), at user's choice.

For the ABC approach, the most adequate representation of LPs uses p.u. values and the peak hourly consumption as reference value. Therefore, for any metered LP or TLP, the maximum value is equal to unity. On the other hand, due to specific mechanisms of the crossover and mutation operators, each time such an operator is applied a de-normalization of the TLPs occurs and a re-normalization is required.

The initial drone population is generated using the following procedure: for a given number of TLPs, denoted by NT, a sequential selection procedure is applied to identify the first NT metered LPs, which are the most dissimilar one each other and with respect to the ones already selected in the previous steps of this procedure. The selected LPs will be used to generate the entire population of drones by adding a white noise.

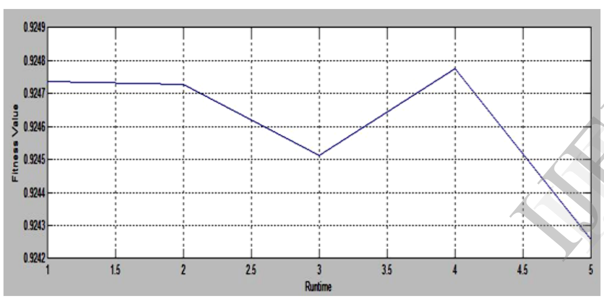

Fig.2. Changes of Fitness function with number of runs

6. RESULTS AND DISCUSSIONS:

The ABC algorithm for the LP clustering problem was approached using a database of metered LPs from 2 consumer categories, (i) Residential and (ii) local industrials. The sets of residential-type and local industrial types LPs from this dataset were specially considered to emphasize specific issues related to the use as fitness function of metrics (3) or (4). Metered LPs for the above customer types were collected for a month, but the numerical analysis that follows was conducted only for weekday LPs. These datasets were used to run the ABC algorithm in different hypothesis.

During the calibration stage of the tests, the values of the parameters used by the ABC algorithm were established using as fitness function metric (4).

Hypothesis I-Fitness function based on metric :

The average distances between metered LPs and associated TLPs for chromosomes with 5 or 6 clusters /TLPs. The two categories of residential consumer (RES-1) the change are significant: from average distances of 0.0043 for the 6 clusters-case to an average distance of 0.0072 for the 5 clusters-case. The total average distance has a decreasing trend when increasing the number of clusters. Such a behavior is normal, since a higher number of clusters implies a lower number of metered LPs associated to a specific cluster and, hence, a lower value of the distance between metered LPs and the associated TLP.

Hypothesis II-Fitness function based on metric:

For this case, the average distances between metered LPs and associated TLPs. Average distances for 5 and 6 clusters / TLPs preserve the same general trends as in Hypothesis I, but values are higher, since the fitness function from metric (4) simultaneously optimizes both distances between metered LPs and TLPs (being minimized) and distances between TLPs (being maximized). The result is a compromise between the two types of distances, which translates into a constant increase of type-distances, but with a more pronounced upward trend for the second type(up to 0.0139 and 0.0104).

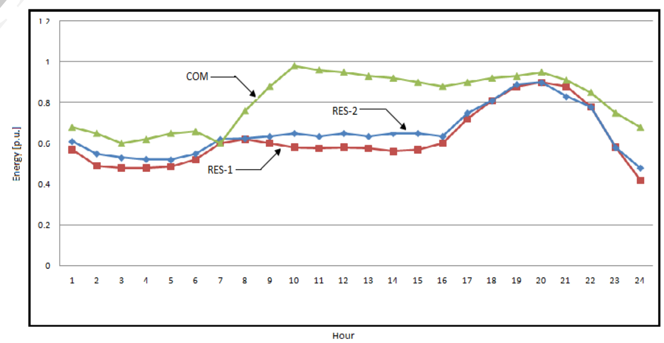

Fig.3. TLPs identified by the ABC algorithm, for a fitness function: 3

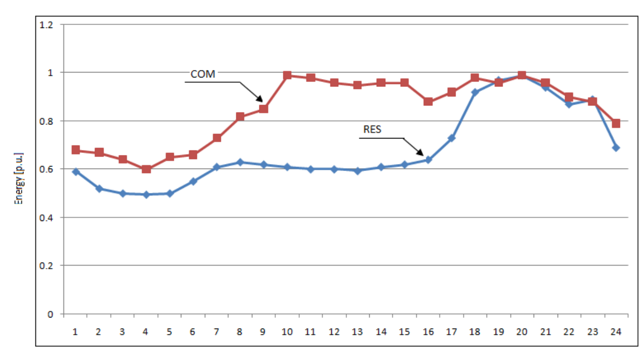

Fig.4. TLPs identified by the ABC algorithm, for a fitness function . 4

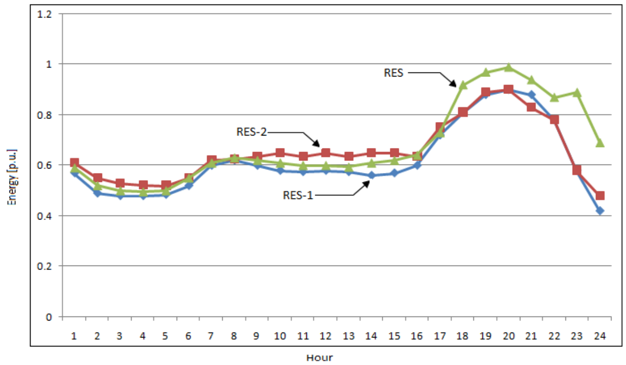

Fig.5.TLPs for residential consumer category generated for hypothesis I (RES-1 and RES-2) and Hypothesis II (RES)

Based on representations from Fig. 3-5 and since for both hypothesis (I and II) the TLPS produced by the ABC algorithm for the rest of consumer categories (RES-1,RES-2and Commercial) are highly similar, as shown in Fig. 3 and Fig. 4, we conclude that the optimal solution for the LP clustering problem discussed in this paper with 5 clusters / TLPs and a fitness function computed based on metric (4). Results are comparable to those presented in [10]. However, the new LP clustering method, based on the ABC algorithm, can be easily implemented as a clustering technique, with high robustness properties. Moreover, the proposed methodology has the advantage of requiring calibration for fewer comparing to the alternative approach, where six parameters must be calibrated (2 parameters for the fuzzy learning rates, and 4 parameters for the we ighting windows around peak and valley load hours).

7. CONCLUSIONS:

Artificial Bee Colony Optimization is inspired by the foraging behavior of honey bees. This paper adopted the swarm intelligence based algorithm like ABC optimization algorithm to search the three consumer categories from selected area. The control aspect of the study depends on the shape of the LPs which is monitored, calibrated and recorded. The results clearly indicate that the proposed algorithm has significant implications with its efficient and stable nature of the structure in handling the database. Therefore, it is evident that new LP clustering approach has the potential and efficiently in addressing metering issues, With little efforts by manipulating the required parameters to obtain the desired goal. In light of this results, it is possible to extend further on these investigations to develop unique ABC Algorithm where in both TLPs and the number of cluster with simultaneous fitness function integrated in the investigation of metering.

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