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LOAD PROFILE CLUSTERING: AN ALGORITHMIC APPROACH WITH IMPROVED REPLACEMENT IN BEE OPTIMIZATION ALGORITHM

K. Kalyani[1] and T. Chakravarthy[2]
[1]*Department of Computer Science, T.U.K. Arts College, India*
E-mail: kkalyasingh@gmail.com
[2]*Department of Computer Science, A. Veeriya Vandayar Memorial Sri Pushpam College, India*
E-mail: tcvarthy@gmail.com

Abstract

The chief aim of this paper is to develop an effective approach to the issue of load profile clustering by applying Improved Replacement In Bee Optimization algorithm (IRIBO). While, intelligent metering solutions like Automated Meter Reading (AMR), Automated Meter Infrastructure (AMI) are in place to address the current issues prevailing in the domain of electricity markets, algorithm using Improved Replacement In Bee Optimization has been proved beneficial and uncomplicated to apply within a selective database. In this study Load Profile (LP) clustering distribution networks based on the shape of the load profile was studied for fitness function in the selected LP clustering. The results clearly indicate that LP clustering has advantages in providing metering solutions to consumers who do not possess digital metering which can be easily operated with trivial changes in the calibrations.

Keywords:

Load Profiling, Honey Bee Modeling, Improved Replacement In Bee Optimization Algorithm, Clustering Techniques

1. INTRODUCTION

The contemporary scenario of electricity market is flowing with a range of distribution 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 extensively adopted to facilitate customers access the retail market and for tariff development purposes. Perhaps, this technology categorizes customers based on the shape of the year load profiles and generates Typical Load Profile (TLP) 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 [1, 2, 3]. The present scenario of electricity market is rolling with a range of intelligent maps, neural networks, fuzzy systems, statistical methods or more recently, the support Vector Clustering approach [4, 5, 6, 7]. This study proposes a new approach to the LP clustering by applying Improved Replacement In Bee Optimization (IRIBO) algorithm. Furthermore, due to the robustness and originality of this method. There are significant benefits like product quality of the results with effortless and trivial 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. Although data clustering aims to find structures in heterogeneous collection of data, these structures describe groups of data within 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

Load Profile is a broad term that can refer to a number of different forms of data. It can refer to demand and consumption data or it can be a reference to derived data types, such as Regression and Profile Coefficients. However, all these data types have one thing in common that they represent the pattern of electricity usage of a segment of supply market customers. A load profile gives the Half-Hourly (Settlement Period) pattern or ‘shape’ of usage across a day (Settlement Day), and the pattern across the settlement year, for the average customer of each of the eight profile classes. It is the proportion of demand in each settlement period that is of interest to the Settlement System [8, 9].

Cluster exploration is a term used to designate a family of statistical measures specifically designed to notice classifications within complex data sets. The aim of cluster analysis is to bunch objects into clusters so that objects within one cluster share more in common with one another than they do with the objects of other clusters. Consequently, the purpose of the analysis is to arrange objects into relatively similar groups based on multivariate observations. The objective of Clustering data is to capture the structure in a heterogeneous group of data. These hierarchies define 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 extent on the classification used to partition of unambiguous and ambiguous data. While, investigators in the behavioral and social sciences are often interested in clustering people, clustering on human objects is common in other disciplines [10].

Thereby, clustering algorithm is used to determine a load profile type and to analyze the demand load in a distribution substation. It is also important to understand the difference between clustering (unsupervised classification) and discriminate analysis (supervised classification). In supervised classification, a collection of labelled (reclassified) patterns are provided. Nevertheless, the issue is to label a newly encountered, yet unlabelled, pattern. Perhaps, the given labelled (training) patterns are used to study the descriptions of classes that in turn are used to label a new pattern. In the case of clustering, the struggle is to group a given collection of unlabelled patterns into meaningful clusters. In a sense, labels are associated with clusters also, but these category labels are data driven that is, they are obtained solely from the data. For instances, clustering algorithms can be applied in many fields such as Web Optimization, Finance, Image Processing, Marketing, Biology, Libraries, Insurances, City planning, Earthquake studies etc.,[11].

3. SIGNIFICANCE OF LOAD PROFILE CLUSTERING

The clustering problem defined in this paper refers to the load description based on electricity distribution network and one of the consumer models is Typical Load Profile. A TLP explain the hourly values of electricity consumption on a daily basis and associated to consumer category. TLPs can be delineated for residential, commercial, industrial and agriculture. Most widely used approach to structure TLP consist of gathering actual LP for various consumer categories, metered in network supply points and process them using clustering algorithm to build TLPs [10, 11]. In order to setup a TLP portfolio for any public utility, it must define a set of TLP that can accurately provide load characteristics for all consumers in its self as a network. If the portfolio includes the maximum TLP and extensive consumers, then, it is the best representation of consumers in terms of accuracy.

4. EXISTING APPROACHES OF HONEY BEE MATING OPTIMIZATION

The mating-flight may be considered as a set of transitions in likely solutions where the queen moves among the similar states in some speed and mates with the drone encountered at each state probabilistically [12, 13, 14]. At the beginning of flight, each queen is initialized by an amount of energy and if this amount reaches a threshold or Zero, or even spermatheca has been filled, the queens will return to the nest. In this algorithm, workers' task is watching broods. In developed algorithm, workers are implemented as heuristic functions which cause fitness of broods to be increased. A drone mates with a queen probabilistically using the function as $PQ\text{-}D = exp(-|FQ - FD| / SP)$.where $Prob(Q, D)$ is the probability of adding the sperm of drone D to the spermatheca of queen Q (that is, the probability of a successful mating); (f) is the absolute difference between the fitness of D that is $f(D)$) and the fitness of Q that is $f(Q)$); and $S(t)$ is the speed of the queen at time t. It is apparent that this function acts as an annealing function, where the probability of mating is high when either the queen is still in the start of her mating-flight and therefore her speed is high, or when the fitness of the drone is as good as the queen's. After each transition in space, the queen's speed $S(t)$, and energy, $E(t)$ decay using the following HBMO algorithm.[12,13]

i. The algorithm starts with the mating-flight, where a queen (best solution) selects drones probabilistically to form the spermatheca (list of drones).
ii. A drone then selected from the list at random for the creation of broods. Creation of new broods (trial solutions) by cross-overing the drones' genotypes with the queen's.
iii. Use of workers (heuristics) to conduct local search on broods (trial solutions).
iv. Adaptation of workers fitness based on the amount of improvement achieved on broods.
v. Replacement of weaker queens by fitter broods.

The algorithm starts with three user-defined parameters and one predefined parameter. The predefined parameter is the number of workers, representing the number of heuristics encoded in the program. The three user-defined parameters are the number of queens, the queen's spermatheca size and the number of broods that will be borne by all queens.

4.1 LOAD PROFILE TECHNIQUE BASED ON HBMO

The electricity load profiles can be created based on the customer usage electricity in regular intervals for accurate measurement of electricity usage. Predict the electricity usage based on the honey bee optimization algorithm for the continuous representation of the data can be varying according to the electricity usage and different meter based on the customer type of usage. The prediction can be normally in the monthly basis and the prediction can be based on the readings of the meters and the prediction cannot be accurate. So, load profile technique can be used for the hourly based measurement of electricity.

The load profile technique can be used for usage of electricity predicted the over time usage of electricity. The dataset collection based on the measurement of current usage by the customer can be categorized as load profiles and the measurement of current in the hourly basis can be considered as the load profiles and the total amount of electricity used can be considered as the Total load profiles. The similar data between metered load profiles and the total load profiles can be calculated and the distance between the Total Load Profiles (TLP) can be calculated and the distance between Total Load profiles can be reduced using HBMO based on the fitness function. The implementation of HBMO algorithm to the LP clustering problem was studied for two distance metrics used as fitness function. Fitness function based on the total average distance between metered LPs and TLPs and fitness function based on the average distance between TLPs. IRIBO also calculate the average fitness function using LP and TLPs. The implementation of the IRIBO algorithm to the LP clustering problem uses fitness function [13].

5. APPLICATION OF IRIBO ALGORITHM TO LOAD PROFILE CLUSTERING

In the IRIBO algorithm, the LP can be represented as the queen and the TLP can be represented as the drones. The fitness function can be taken in the predicted Indian dataset and the dataset can be categorized as per the corresponding field. Choose the field and predicted the sum of average value in the dataset and it can be represented as the drones and peak three average values next to drones can be represented as the queen to optimize the LP values in the electricity to minimize the wastage of the electricity. The queen replacement with the drone can be based on the top best three values can be considered as the queen values [14, 15].

The average value can be represented as the TLP value and it can be considered as the drone and the next three nearest consecutive values can be taken as the queen value. The difference between the TLP can be taken as the reference value and it can be replaced by next consecutive maximum value and it can be represented as the queen. The metered TLP value represented can be minimized and the queen value of LP can be maximized.

$$ST(n) = \frac{E_M, n}{(P_{EH}, n+\alpha)Log\mu}\left(E^{\lambda(m)} - 1\right)$$

$$\lambda(m) = \frac{E_M, n - E_S, n}{E_M, n}$$

where, α and λ are the constants

To ensure that only nodes with sufficient energy sustainability are selected as cluster heads, the nodes with $ST(n)$ below the average are eligible to be cluster head candidates for this round.

5.1 IRIBO-ALGORITHM

Phase 1: Random Cluster should be formed by using enhanced KNN Algorithm.

Phase 2: The next step is **sustainability**. It is considered for each tuple to analyze the **lifespan** of the cluster.

$$ST(X) = \frac{E_X, X}{(P_{EH}, X+\alpha)Log\mu}\left(E^{\lambda(X)} - 1\right) \tag{1}$$

$$\lambda(x) = \frac{E_X, X - E_x, X}{E_X, X} \tag{2}$$

where, α and λ are the constants

Phase 3: Analyze the Relationship announcement array of data

$$ETX(k, d) = EelecK + Efskd^2 \tag{3}$$

Phase 4: Analyze the Relationship Delivery array of data

$$ERX(k) = EelecK \tag{4}$$

Phase 5: Predict a Cluster Head for each unequal cluster by using the sustainability Value which is calculated in Phase 2.

Phase 6: Derive the fitness value of each unequal clusters by using the following steps:

Step 1:

$$F = Af_1(Cl_p) + Bf_2(Cl_p) + Cf_3(Cl_p) + Df_4(Cl_p)$$

where, A, B, C, D are constants with 0.2, 0.5, 0.2, 0.1 consequently.

Step 2:

$$f_1(Cl_p) = \sum_{j=1}^{\beta}\left[\left(\sum_{i=1}^{\alpha_j} d_{ijhj}\right) + d_{hjbs}\right] \tag{5}$$

Step 3:

$$f_2(Cl_p) = \sum_{j=1}^{\beta}\left[\left(\sum_{i=1}^{\alpha_j}\frac{ST(ij)}{ST(hj)}\right)\right] \Big/ k \tag{6}$$

Step 4:

$$f_3(Cl_p) = \sum_{j=1}^{\beta}\frac{\lfloor d_{hjbs}\rfloor}{} \Big/ \sum_{j=1}^{\beta}\sum_{i=1}^{\alpha_j}\left[d_{ijbs}\right] \tag{7}$$

Step 5:

$$f_4(Cl_p) = 1\sum_{j=1}^{\beta}\sum_{i=1}^{\alpha_j} \mathrm{E}_{TX}\left(1, d_{ijhj}\right) + \alpha_j \mathrm{E}_{RX}(1) \tag{8}$$

Phase 7: Repeat Phase 3 to Phase 6 to form various Clusters.

where, function f_1 is the sum of Euclidean distances of cluster member to its cluster head and cluster heads to the base station (*BS*), Cl_p is a chromosome in the current round, α_l (l = 1,…, β) is the number of cluster members, β is the number of clusters, d_{ijhj} is the Euclidean distance from node i in cluster j to its cluster head, d_{hjbs} is the Euclidean distance from j^{th} cluster head to the BS. Function f_2 is the ratio of the average energy sustainability of cluster members with its cluster head. Function f_3 is the ratio of the average Euclidean distance of the cluster heads to the BS with the sum of Euclidean distance of all the sensor nodes to the BS. Function f_4 is the inverse of transmission energy in intra-clusters, on the side inter-cluster transmission energy will be discussed in next section. The constants A, B, C, D are predefined constants used to weight the contribution of each of the sub objectives and A + B + C + D = 1. The fitness function defined above has the objective of simultaneously minimizing the intra-cluster distance between nodes and their cluster heads, as quantified by Q_1 and of maximizing the cluster head's energy sustainability in its cluster as quantified by Q_2; and of producing cluster with unequal size as quantified by Q_3; and also of optimizing the energy dissipation in the clusters as quantified by Q_4. According to the fitness function, a small value of Q_1, Q_2 suggests compact clusters with the optimum set of nodes that have sufficient energy to perform the cluster head tasks. A small value of Q_3 means that the size of the clusters located closer to the BS is smaller. A small value of Q_4 shows that the formed clusters are more energy efficient.

6. RESULTS AND DISCUSSIONS

The Improved Replacement In Bee Optimization algorithm (IRIBO) for the load profile clustering problem was approached using a database of metered LPs from different consumer categories in the dataset as per the Indian context. The dataset categories are i) Residential two substations (Resi-1 and Resi-2), ii) Industrial (Ind-1 and Ind-2), iii) Agriculture (Agri-1 and Agri-2) iv) Commercial such as six categories are Hospital, super market, Theatre, University, Bank, Hostel. The dataset were specially considered to the use of fitness function. The overall dataset is evaluated by the attributes, the attribute statistics representations are as follows. KW, KVA, Type, Sector, ServiceID.

The above datasets were collected for a month and used to run the IRIBO algorithm in different fitness values. Based on the representation of attributes the TLPs produced by the IRIBO algorithm for the consumer categories. We conclude that the optimal solution for the LP clustering problem discussed in this paper and uses a chromosomes encoding scheme with 12 clusters/TLPs and a fitness function computed. Results are comparable to others, the new LP clustering method based on IRIBO algorithm can be easily implemented with high robustness properties.

The IRIBO algorithm will also forms the Association Rule for any dataset the following rules are formed for the given dataset.

1) hospital2 = 2,8 576 ==> indus1 = 10,15 576
2) indus1 = 10,15 576 ==> hospital2 = 2,8 576
3) agri1 = 0,2 369 ==> indus1 = 10,15 369
4) agri2 = 0,2 369 ==> indus1 = 10,15 369
5) agri2 = 0,2 369 ==> agri1 = 0,2 369
6) agri1 = 0,2 369 ==> agri2 = 0,2 369
7) agri1 = 0,2 369 ==> hospital2 = 2,8 369
8) agri2 = 0,2 369 ==> hospital2 = 2,8 369
9) agri1 = 0,2 agri2 = 0,2 369==>indus1 = 10,15 369
10) indus1 = 10,15 agri2 = 0,2 369 ==> agri1 = 0,2 369

Minimum support: 0.6 (346 instances)

Minimum metric <confidence>: 0.9

Number of cycles performed: 8

Generated sets of large itemsets:

Size of set of large itemsetsL (1): 6

Size of set of large itemsetsL (2): 11

Size of set of large itemsetsL (3): 8

Size of set of large itemsetsL (4): 2

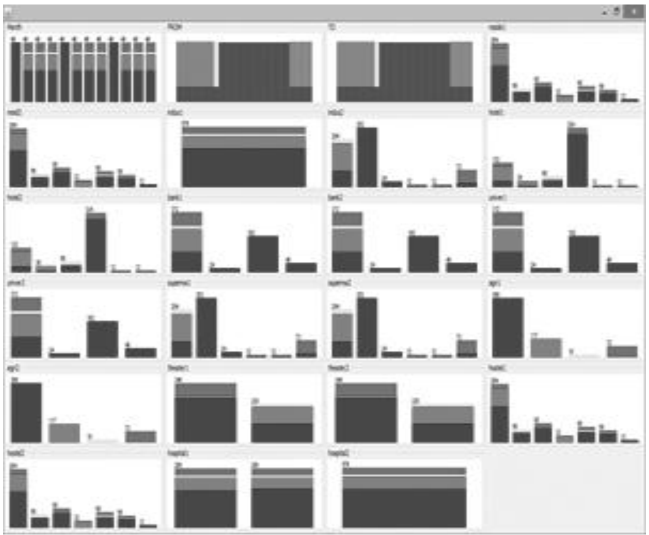

Fig.1. Load Profile Clustering of various Fields

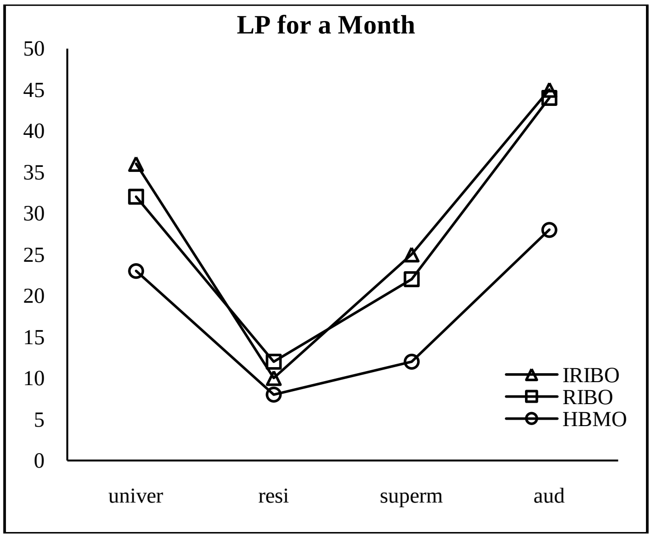

Fig.2. IRIBO

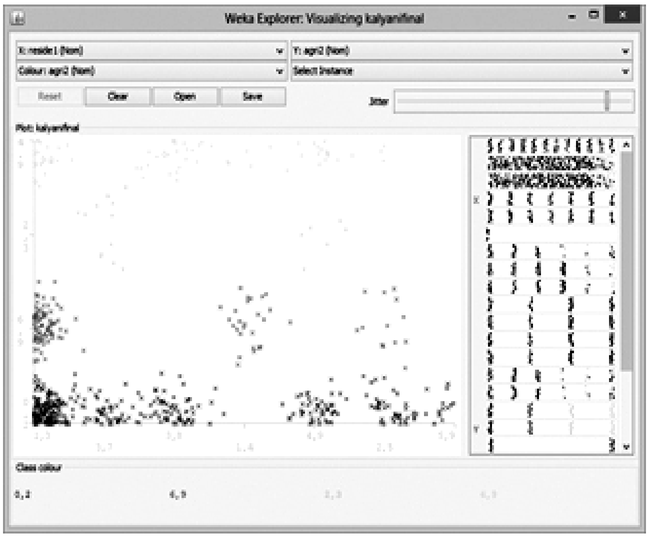

Fig.3. Load Profile Clustered Data Representation of residential and agriculture

Table.1. Sample dataset

Viewer

Relation: kalyanifinal

No.	1: Month Nominal	2: FROM Nominal	3: TO Nominal	4: reside1 Nominal	5: resid2 Nominal	6: indus1 Nominal	7: indus2 Nominal	8: hotel1 Nominal	9: hotel2 Nominal	10: bank1 Nominal	11: bank2 Nominal	12: univer1 Nominal	13: univer2 Nominal	14: superma1 Nominal	15: superma2 Nominal	16: agri1 Nominal	17: agri2 Nominal	18: theater1 Nominal	19: theater2 Nominal	20: ho Nom
175	april	15:00:00	15:30:00	1,3	1,3	10,15	8,18	4,10	4,10	5,12	5,12	5,12	5,12	8,18	8,18	0,2	0,2	12,25	12,25	1,3
176	april	15:30:00	16:00:00	1,3	1,3	10,15	8,18	4,10	4,10	5,12	5,12	5,12	5,12	8,18	8,18	0,2	0,2	12,25	12,25	1,3
177	april	16:00:00	16:30:00	1,3	1,3	10,15	8,18	4,10	4,10	5,12	5,12	5,12	5,12	8,18	8,18	0,2	0,2	12,25	12,25	1,3
178	april	16:30:00	17:00:00	4,9	4,9	10,15	8,18	4,10	4,10	5,12	5,12	5,12	5,12	8,18	8,18	0,2	0,2	12,25	12,25	4,9
179	april	17:00:00	17:30:00	4,9	4,9	10,15	8,18	4,10	4,10	5,12	5,12	5,12	5,12	8,18	8,18	0,2	0,2	12,25	12,25	4,9
180	april	17:30:00	18:00:00	4,9	4,9	10,15	8,18	4,10	4,10	5,12	5,12	5,12	5,12	8,18	8,18	0,2	0,2	12,25	12,25	4,9
181	april	18:00:00	18:30:00	4,9	4,9	10,15	8,18	4,10	4,10	4,6	4,6	4,6	4,6	8,18	8,18	0,2	0,2	12,25	12,25	4,9
182	april	18:30:00	19:00:00	4,9	4,9	10,15	8,18	4,10	4,10	4,6	4,6	4,6	4,6	8,18	8,18	0,2	0,2	12,25	12,25	4,9
183	april	19:00:00	19:30:00	4,9	4,9	10,15	2,8	4,10	4,10	4,6	4,6	4,6	4,6	2,8	2,8	0,2	0,2	12,25	12,25	4,9
184	april	19:30:00	20:00:00	4,9	4,9	10,15	2,8	4,10	4,10	4,6	4,6	4,6	4,6	2,8	2,8	0,2	0,2	12,25	12,25	4,9
185	april	20:00:00	20:30:00	4,9	4,9	10,15	2,6	4,10	4,10	1,3	1,3	1,3	1,3	2,6	2,6	4,9	4,9	12,25	12,25	4,9
186	april	20:30:00	21:00:00	4,9	4,9	10,15	2,4	4,10	4,10	1,3	1,3	1,3	1,3	2,4	2,4	4,9	4,9	12,25	12,25	4,9
187	april	21:00:00	21:30:00	4,9	4,9	10,15	1,2	4,10	4,10	1,3	1,3	1,3	1,3	1,2	1,2	4,9	4,9	12,25	12,25	4,9
188	april	21:30:00	22:00:00	4,9	4,9	10,15	1,2	4,10	4,10	1,3	1,3	1,3	1,3	1,2	1,2	4,9	4,9	12,25	12,25	4,9
189	april	22:00:00	22:30:00	4,9	4,9	10,15	1,2	3,5	3,5	1,3	1,3	1,3	1,3	1,2	1,2	4,9	4,9	12,25	12,25	4,9
190	april	22:30:00	23:00:00	1,4	1,4	10,15	1,2	3,4	3,4	1,3	1,3	1,3	1,3	1,2	1,2	4,9	4,9	12,25	12,25	1,4
191	april	23:00:00	23:30:00	1,4	1,4	10,15	1,2	1,3	1,3	1,3	1,3	1,3	1,3	1,2	1,2	4,9	4,9	12,25	12,25	1,4
192	april	23:30:00	0:00:00	1,4	1,4	10,15	1,2	1,3	1,3	1,3	1,3	1,3	1,3	1,2	1,2	4,9	4,9	12,25	12,25	1,4
193	may	0:00:00	0:30:00	2,5	2,5	10,15	0,2	1,3	1,3	1,3	1,3	1,3	1,3	0,2	0,2	0,2	0,2	12,25	12,25	2,5
194	may	0:30:00	1:00:00	2,5	2,5	10,15	0,2	1,3	1,3	1,3	1,3	1,3	1,3	0,2	0,2	0,2	0,2	12,25	12,25	2,5
195	may	1:00:00	1:30:00	2,5	2,5	10,15	0,2	1,3	1,3	1,3	1,3	1,3	1,3	0,2	0,2	0,2	0,2	2,4	2,4	2,5
196	may	1:30:00	2:00:00	2,5	2,5	10,15	0,2	1,3	1,3	1,3	1,3	1,3	1,3	0,2	0,2	0,2	0,2	2,4	2,4	2,5
197	may	2:00:00	2:30:00	2,5	2,5	10,15	0,2	1,3	1,3	1,3	1,3	1,3	1,3	0,2	0,2	0,2	0,2	2,4	2,4	2,5

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Table.2. Clustered Data

Cluster centroids:												
Attribute	**Full Data (576)**	**Cluster# 0 (30)**	**1 (49)**	**2 (32)**	**3 (13)**	**4 (10)**	**5 (24)**	**6 (21)**	**7 (36)**	**8 (128)**	**9 (48)**	**10 (45)**
reside1	1,3	1,3	3,8	2,5	1,3	2,5	1,3	2,5	3,7	1,3	3,8	3,7
resid2	1,3	1,3	3,8	2,5	1,3	2,5	1,3	2,5	3,7	1,3	3,8	3,7
indus1	10,15	10,15	10,15	10,15	10,15	10,15	10,15	10,15	10,15	10,15	10,15	10,15
indus2	8,18	0,2	1,2	8,18	0,2	1,2	0,2	0,2	8,18	8,18	8,18	0,2
hotel1	4,10	2,5	4,10	4,10	3,8	1,3	1,3	1,3	4,10	4,10	4,10	3,8
hotel2	4,10	2,5	4,10	4,10	3,8	1,3	1,3	1,3	4,10	4,10	4,10	3,8
bank1	1,3	1,3	1,3	5,12	1,3	1,3	1,3	1,3	2,5	5,12	4,6	1,3
bank2	1,3	1,3	1,3	5,12	1,3	1,3	1,3	1,3	2,5	5,12	4,6	1,3
univer1	1,3	1,3	1,3	5,12	1,3	1,3	1,3	1,3	2,5	5,12	4,6	1,3
univer2	1,3	1,3	1,3	5,12	1,3	1,3	1,3	1,3	2,5	5,12	4,6	1,3
superma1	8,18	0,2	1,2	8,18	0,2	1,2	0,2	0,2	8,18	8,18	8,18	0,2
superma2	8,18	0,2	1,2	8,18	0,2	1,2	0,2	0,2	8,18	8,18	8,18	0,2
agri1	0,2	6,9	4,9	0,2	6,9	0,2	0,2	6,9	0,2	0,2	0,2	0,2
agri2	0,2	6,9	4,9	0,2	6,9	0,2	0,2	6,9	0,2	0,2	0,2	0,2
theater1	12,25	2,4	12,25	12,25	2,4	12,25	12,25	2,4	2,4	12,25	12,25	2,4
theater2	12,25	2,4	12,25	12,25	2,4	12,25	12,25	2,4	2,4	12,25	12,25	2,4
hostel1	1,3	1,3	3,8	2,5	1,3	2,5	1,3	2,5	3,7	1,3	3,8	3,7

7. CONCLUSION

This paper presents an efficient method for the classification and load profiling of distribution network customers. The proposed method was implemented as a MATLAB program and tested with real data and also it was tested with Weka. The result showed that the IRIBO algorithm can classify customers into well separated clusters according to their electricity consumption data, and clearly indicate that the proposed IRIBO 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 in efficiently addressing metering issues. Correspondingly, with little efforts by manipulating the required parameters it is possible to obtain the desired results and reach the goal. In light of this result, it is certainly possible to extend further on these investigations to develop Improved Replacement In Bee Optimization Algorithm where in both TLPs and the number of clusters with simultaneous fitness function integrated in the investigation of metering. It was proved earlier that, the resulting customer classification is more accurate than the alternative classification methods .The snapshots are clearly indicated that the proposed IRIBO Clusters and load profile data more accurately than the existing RIBO which was also implemented and it also proves that IRIBO is also accurate than the most popular HBMO Model.

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