March - April 2020
ISSN: 0193-4120 Page No. 4722 - 4734

Energy Profiling and Residential Load Shifting Mechanism with Cost Reduction using Genetic Algorithm

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Abstract

A growing number of residential consumers despite high electricity costs in the provinces largely impart to the overall power market situation in the Philippines resulting in high emission generating units adding harm to the environment, coal dependency and supply shortage, especially during summer. Demand Side Management (DSM) aims to encourage consumers to use less energy during peak times. Demand Response (DR) is a type of DSM towards conserving the use of energy to reduce system peak demand and operational cost. This paper proposed a metaheuristic demand response mechanism for residential consumers to reduce consumers' peak demand and minimize electricity cost via Genetic Algorithm load shifting without affecting the consumers' conveniences. Further, the paper assumed that the energy market is existing and published hourly energy prices a day ahead and that the hourly demand of household consumers is known through a load forecast using Weighted Least Square. Furthermore, the flat iron and washing machine are the identified appliances the consumers' willing to use during non-peak hours. The process was simulated through MATLABr2018a in generating the best-fit combinations for load shifting.

Index Terms: *Demand Response, Genetic Algorithm, Hierarchical Clustering, Load Shifting*

I. INTRODUCTION

The Demand Side Management (DSM) is to plan, develop, and implement DSM programs whose objective is to shape efficiency as well as optimized daily and seasonal load profiles of consumers to realize or achieved better overall system of utilization [1]. To drive such programs, Demand Response and Energy Efficiency are the key vehicles towards these measures. DR programs are either price based, or incentives based. Price based programs are further classified to Time of Use (TOU), Real Time Pricing (RTP) and Critical Peak Pricing. TOU is the rate of different electricity prices at different periods of time with a day reflecting the average power cost at that time. In RTP, programs fully expose customers to the variability and volatility of costs in the wholesale power market. Rates charged for electricity reflect the actual supply costs to the utility for each hour of the day. The prices are provided to customers anywhere from an hour; to as much as 24 hours ahead of time is a variation of TOU tariffs that tries to reflect the uncertainty and volatility of electricity supply costs. The CPP tariff adds a time-dependent rate several times higher than normal rate to either standard, or TOU rates, during peak periods [2]. Incentive Based Programs are further classified to the Emergency Demand Response Program (EDRP), Interruptible/ Curtailable Services (IC), Direct Load Control (DLC), Capacity Market Program(CMP), Demand Bidding and Ancillary Services Market. The latter two are also classified as Market Based Program. Emergency demand response program

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(EDRP) pays retail electricity customers to reduce load during specific times when electric service could be jeopardized. During these declared events, participants are expected, though not obligated, to either reduce electricity consumption or transfer load to an on-site generator for a minimum of four hours. During these emergency program events, performance is based on how much metered load is reduced.

There are several techniques and algorithms to conserve the customers use of energy and reduce the utility's system peak load and operational cost. Pavithra and Priya proposed in 2017 the load - shifting concept for all the shiftable several types of appliances. Load shifting is used to schedule controllable devices of residential customers at various time of the day and Genetic Algorithm (GA) was involved in the averaging of households hourly load profile. MATLAB was used for the simulation of BTM Layout, Bangalore, Karnataka state for an entire week of different working centers that include residential consumers and activity centers likes social club, school, hospital and stores. The authors were concentrated on reducing the cost of the utilities and also the peak response by considering different types of devices used in the area. The consumption for weekdays and weekend activities were compared in terms of average and maximum demand. In the study of energy management via power scheduling, the customers used electricity as per requested benefitting them with lower cost. The retailer is assumed to publish hourly energy prices to its customers in a day ahead fashion by variable pricing scheme and that the customers are aware of their hourly load requirements. To demonstrate the efficacy of the methodology, a metaheuristic formulation minimizing the customers overall energy cost using a genetic algorithm was introduced. The authors concluded that the cost was reduced upon employing GA, but suggested to incorporate the customers' inconveniences, energy retailers' benefit, real-time scenarios instead of day ahead method, multiple appliances and the different modes to refine their formulation [3].

Smart meters, communications networks, and data management systems that enables two-way communication between utilities and customers strengthen the demand response programs. The two - way communications through smart meters will provide the information and options to customers to manage the energy usage and save electricity bills during peak periods. The utility will send notifications to help consumers plan ahead and to ensure that the customers have time to shift or reduce electricity use during these periods and offers incentives for their active participation [4]. However, some of the consumers don't have yet the Automatic Meter Reading (AMR) or most of customers are not installed of Advanced Metering Infrastructure (AMI) at the moment. Further, even though a consumer is installed with such meters, it is very difficult or impossible for a utility to identify the right function to model the consumer's usage behavior due to various uncertainties in usage pattern. The utility has to understand first the consumers' energy consumption patterns to determine the peak demand and the price and exploit this behavior patterns for the program [5] . The current situation in the energy market, particularly in Camarines Sur Electric Cooperative II (CASUREO II), with franchise area of 976 sq. km and a total of 94, 106 captive customer, out of which is 87, 256 residential customers need a program to balance the demand and supply particularly during the summer season. The largest of the 5 substation is located at Naga City with 40MVA and 20MVA substation capacity. The peak demand of the total franchise area last year reached 65.678MW, at a load factor of 58.11% and with a demand annual average growth rate of 5.99%. There is still a growing number of residential customers despite high electricity cost, power interruptions and scheduled brown outs because of preventive maintenance or shortened supply for demand. These things contribute to the overall power market situation in the Philippines resulting to high emission generating units that cause harm to the environment, coal dependency and so on. The energy market needed help to respond to all these problems and little steps can start at the local utilities particularly in the provinces.

This paper will propose a demand response approach designed to residential customers to reduce peak load demand and minimize electricity cost of the electricity customers through load shifting. Specifically, this paper will 1.) forecast the energy usage of residential customers, 2.) cluster them into groups based on the customers maximum demand, 3.) present a load shifting DR mechanism for peak load reduction of load profiles, and 4.) optimize the energy consumption cost of clustered residential customer.

Demand Response program will benefit all the utility stakeholders. The electricity customers need to better understand their electrical consumption behavior and its equivalent cost, hence they will be encourage to properly manage their load and achieve efficiency of its utilization. Moreover, the customer will be able to identify and decide their potential saving by switching to the cheaper periods. Load profiling and clustering the customers will help the utility to improve its operation efficiency and enhance power reliability.

The research is focused on residential households with installed the Automatic Meter Reading (AMR). The retailer procures electricity from the Philippine Electricity Market Corporation (PEMC) and sell to its captive market. Customers load forecast of electricity consumption were based on the consumers previous monthly billing from 2014 - 2018. The utility price changes monthly, thus, the author used the hourly energy price of PEMC for CASURECO II. The lifelines were not included on this study. Lifelines are those with consumption of 40kWh and below monthly. Further, it does not include design and installation of the Home Energy Management Systems (HEMS) nor installation of the AMI. The mode of price information delivery to the customer is also not discussed on this paper.

II. METHODOLOGY

This study is focused on the development of algorithm for a residential demand response program to reduce the energy use and energy cost without impacting the comfort level and the productivity of all utility stakeholders through profiling of loads and optimization of the energy cost. Fig. 1 showed the conceptual framework of the study.

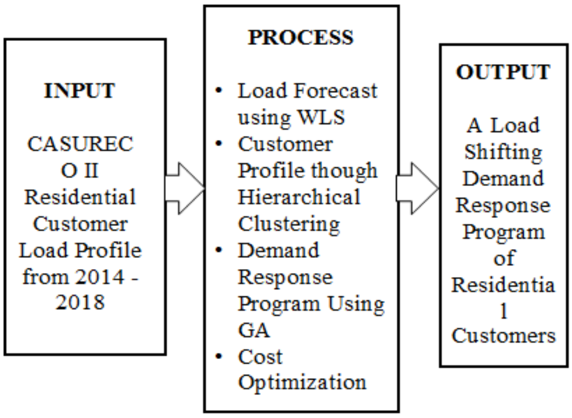

Fig. 1 Conceptual Framework

The data gathered from CASURECO II were used to profile customers according to the pattern of energy usage through hierarchical clustering. This profile will be use to generate a demand response program through Genetic Algorithm. Fig. 2 summarized the various phases in the research.

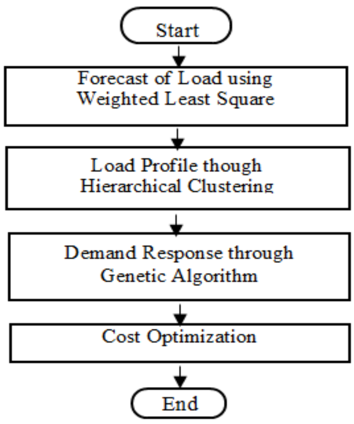

Fig. 2 Flowchart of the Study

March - April 2020
ISSN: 0193-4120 Page No. 4722 - 4734

Load Forecast

Load Forecasting is essential in the planning of the utility operations. These forecasts are essential in the utility's operation as it contributes to the operation savings, maintenance costs, increased reliability of power supply and delivery system, and correct decisions. Demand is assessed by accumulating the consumption monthly, and yearly periods. The load characteristics is normally different between weekdays and weekends and between seasons. The 2014 - 2018 historical demand of residential customers shown in Table 1 were used in the ten-year forecast using the Weighted Least Square (WLS) method.

Weighted Least Square (WLS) Method

The data are assumed to be of equal quality, and therefore has constant variance. Otherwise, the fit may be improperly influenced by the poor quality of data. To improve this fit, WLS regression minimizes the error estimate using the equation

$$s = \sum_{i=1}^{n} w_i (y_i - \hat{y_i})^2$$

where wi are the weights. The weights determine how much each response value influences the final parameter estimates. A high-quality data point influences the fir more than a low – quality data point. Weighing data is recommended if the weights are known. The weights modify the expression for the parameter estimates b in the following way,

$$b = \hat{\beta} = (X^T W X)^{-1} X^T W y$$

where W is given by the diagonal elements of the weight matrix w.

The weights should transform the response variances to a constant value. If variances of the measurement errors are known, then the weights are given by

$$w_i = 1/\sigma_i^2$$

If variances are unknown, specify the weights on a relative scale. In this instance, the weights define the relative weight to each point in the fit but are not taken to specify the exact variance of each point [30].

Table 1 Monthly electricity consumption

CASURECO II Historical Demand (MWh) 2014-2018					
Year / Month	**2014**	**2015**	**2016**	**2017**	**2018**
January	6,199	8,576	9,370	4,606	10,005
February	7,280	7,234	8,619	8,514	10,147
March	8,954	8,956	9,198	8,383	10,232
April	8,125	9,875	10,533	10,793	11,719
May	9,786	10,785	11,760	12,225	12,571
June	9,231	10,993	12,703	12,849	13,081
July	8,729	9,378	10,957	11,323	12,707
August	7,652	8,756	11,629	12,431	13,030
September	8,956	11,458	12,681	12,185	12,878
October	7,564	9,271	10,452	12,277	12,293
November	8,345	8,494	10,185	11,278	12,178
December	7,213	7,452	9,929	10,844	12,749

The Camarines Sur Electric Cooperative II (CASURECO II) have a total of 100,449 residential electricity consumers as of December 2018. Every year, there's a variation between 3 to 5% because of the delinquent consumers. Out of this number, 7% or about 7,030 are lifeline consumers, or those with 40kWh and below monthly consumption. The highest demand last 2018 is at Concepcion Substation with a maximum demand of less than 5,000 kWh. May, June, September and October are the months seen with large demand during the last five years. The drop on the historical data during 2017 was due to the typhoon that dilapidated most of the structures of the local cooperative.

The customers' profile were based on the data gathered from CASURECO II residential customers

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March - April 2020
ISSN: 0193-4120 Page No. 4722 - 4734

which include the peak demand that varies between 6PM to 8PM during weekdays and 12NN to 8PM during weekends. Initially, the individual consumers were grouped according to demand, time of peak and day of peak, substation and household class. Day of peak was grouped from Monday through Sunday. Feeder connection was dependent on the substation location. The cooperative have five substations as shown in Table 2. And lastly, the author consolidated the social class into working class, lower middle class, upper middle class and upper class based on the 2015 Average Annual Family Income and Expenditure by Family Size, by Income Class and by Region of Philippines Statistics Authority. Working class are those blue-collar/clerical jobs, salary range between Php 8,000-15,000 per month. Lower Middle class are those white-collar jobs income range between Php 15,000-50,000 per month. Upper middle class are the professionals with paychecks between Php 50,000-100,000 per month. Upper Class are the executives, presidents and CEOs with earnings of Php 100,000+ per month.Customers' electricity appliances are further categorized into 3 groups [18]:

Shiftable appliances. The operation time of these appliances can be shifted to some other time. This includes dishwashers and washing machines.

Non-shiftable appliances. The operation time of these appliances are fixed. Air – conditioning units, water heater and refrigerators.

Essential appliances. The operation time are predetermined and need constant power. Examples are TVs, and cooking appliances.

In this paper, the shiftable appliances considered by the author after conducting survey deems to be pertinent to the Philippine residential customers apart from washing machine is flat iron.

Table 2 CASURECO II Substations

Substation	Capacity	Location	Feeder Number
1	2 – 20MVA	Villa Concepcion, Naga	2, 3, 8, 5, 1
2	2- 20MVA	Del Rosario, Naga City	51,52,53,54,55,56
3	1-10MVA	Pili, Camarines Sur	21, 22
4	1- 10MVA	Calabanga, Camarines Sur	41, 42
5	1 – 5MVA	Tinambac, Camarines Sur	31, 32

Load Profile and Hierarchical Clustering

Load profiles are patterns of electricity usage for a customer or group of customers over a given period. These profiles are widely used in distribution network analysis, such as network load flow calculation, state estimation, network planning and tariff planning. These are generated using the historical usage data of the customers [19]. The data for profiling customers are based on the data gathered from CASURECO II residential customers. Hierarchical clustering will be use to group these customers according to their energy usage pattern.

Hierarchical clustering creates a tree structure called Dendogram by calculating the similarity of two data sets. The tree is not a single of clusters, but rather a multilevel hierarchy, where clusters at one level are joined at the next level [20]. Hierarchical clustering has an advantage that number of clusters is not need to input arguments. The number of clusters is determined by the cutting position in the binary tree which is chosen either by the maximum distance admissible or by selecting directly the distance corresponding to the desired number of clusters [21].

To perform hierarchical clustering, it is necessary to find the similarity and dissimilarity between every pair of load profiles in the data and then grouping them into binary clusters based in the previously computed similarity matrix [22]. The process is

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March - April 2020
ISSN: 0193-4120 Page No. 4722 - 4734

iteratively repeated by merging the clusters of each level into bigger ones at the upper level until all samples are grouped into expected clusters.

Demand Response Program

Demand Response popularity as means of administering demand side management is continuously thriving in Smart Grid. An energy management for residential customers via power scheduling to minimize the overall cost of individual customers using Genetic Algorithm was proven to be an attractive alternative for a metaheuristic search algorithm [23]. Most of the researches assumed an energy market that published hourly energy prices in a day ahead manner. However on this paper, the study considered traditional local utility without Smart Grid. Thus, the author utilize the real- time Ex- Post Price of Philippine Electricity Market Corporation (PEMC) for CASURECO II. The steps of the proposed demand response program include:

1. Input data taken from the survey of residential customers' appliances and usage.
2. Preparation of target demand cluster.
3. Monthly Shiftable load of selected customer as inputs to Genetic Algorithm
4. Output of the algorithm is the load shifted of the customer at the optimized price.

Genetic Algorithm

Genetic Algorithm is an algorithm which includes genetic properties. It is used to generate solutions for optimization. The process will start by generating a random of 10,000 chromosomes from the clustered residential customers. To get the fitness, it evaluates the fitness f(x) of each chromosome in the population. In creating the new population, the following steps will be followed until the new population is completed. In this study, the following steps follow the MATLAB functions.

Step 1: Selection. Two parent chromosomes will be selected from a population according to their fitness, usually the better the fitness, the bigger is the chance to be selected. Selection options in this study specify how the genetic algorithm chooses parents for the next generation.

Step 2: Crossover. To form new offspring (children), the parents will perform crossover probability, otherwise, offspring will be the exact copy of parents. Crossover settings include scattered, heuristic, single point, two point and arithmetic. The crossover single point, two point and scattered do not work with linear constraints. The population will not yield the required constraints.

Step 3: Mutation. The mutation probability will mutate new offspring at each locus. Mutation options specify how the genetic algorithm makes small random changes in the individuals in the population to create mutation children. Mutation provides genetic diversity and enables the genetic algorithm to search a broader space.

Step 4: Then, place the new offspring in the new population.

To replace population, generate further run of the algorithm. If the end condition is satisfied, then end and return the best solution in current solution. To create new fit, repeat the process from step 2.The generation indicated the closeness of the individual. As the number of generation increases, the individuals in the population get closer together and approach the minimum point. It will stop at the maximum number of generations indicated.

Cost Optimization

The energy consumption of customers for shiftable appliances are not only prices dependent but also on the costumers activities. It is important to know the customers energy behavior to optimize the price for the next month.

In this study, the optimization criteria considered is the optimized energy of clustered customer. Mathematically, the problem was defined [3]as:

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TEST Engineering & Management

March - April 2020
ISSN: 0193-4120 Page No. 4722 - 4734

$$\min_{cost} \sum_{\substack{C \in Cust \\ M \in Mo}} DEMGA[C][M] * COST[M]$$

Subject to

$$\sum_{\substack{C \in Cust \\ M \in Mo}} DEMGA[C][M] = TOTDEM\,[C]$$

$$\sum_{\substack{C \in Cust \\ M \in Mo}} DEMGA[C][M] \leq TOTPOW\,[M]$$

$$DEM[C][M]_{min} \leq TOTDEM[C][M] \leq DEM[C][M]_{max}$$

where DEMGA[C][M] indicates the demand required by customer C in month M, COST[M]denotes the electricity price for the month given by the utility, Customer is the set of customers in a cluster, M is the month considered, TOTDEM[C] is the total demand given by the customer, TOTPOW is the total demand supply by the utility in a month[3], 〚DEM[C][M]〛_min is the lowest demand of a customer in a cluster before GA and 〚DEM[C][M]〛_max is the highest demand of a customer in the cluster before GA.

III. RESULTS AND DISCUSSIONS

Load Profile and Load Forecast

Initially, the residential customers of CASURECO II were filtered according to their demand, time of peak, day of peak, location or substation connection and class using MATLAB. The demand reflected was January 2019. Considering Sunday, the whole CASURECO II residential customers are peaking between 12NN to 8PM. There are 1,820 customers peaking at 12NN, 1,806 at 1PM, 1,818 at 2PM, 1,766 at 3PM, 1,740 at 4PM, 1,741 at 5PM, 1,851 at 6PM, 1,856 at 7PM and 1, 778 at 8PM. Further, considering the peak at 12NN, out of the 1,820 customers, 123 of them belongs to upper class, 683 belong to upper middle class, 665 belong to lower class and 349 are working class. The two-figure illustrated how the filtering worked. The left box of Figure 3.5 showed the total number of customers filtered according to days of the week: 1 is Sunday, 2 is Monday, 3 is Tuesday, 4 is Wednesday, 5 is Thursday, 6 is Friday and 7 is Sunday. The vertical axis is the maximum demand of each customer per month. The right box was further filtered to 795 lower middle class customers having peak during 7PM located at substation 2. Fig. 3 and Fig. 4 shows customers initially filtered according to their feeder connection, consequently, the right box showed 511 upper middle-class customers with maximum demand during Saturdays at 1PM.

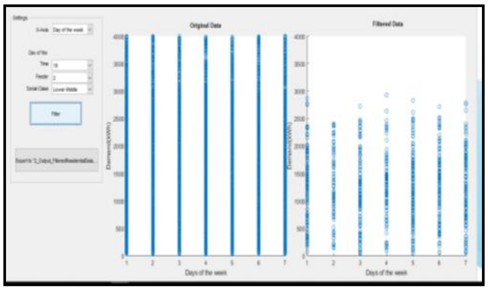

Fig. 3 Residential Customers filtered according to the day of peak, time, feeder connection and the social class.

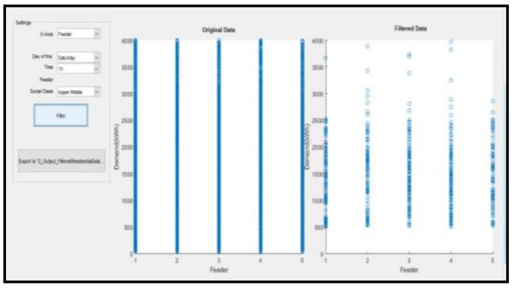

Fig. 4 Residential Customers filtered according to the feeder, day of peak, time of peak and the social class.

The monthly demand of all residential customers was forecasted using the Weighted Least Square (WLS) in MATLAB. The forecasted energy displays a linear increase in the customers demand as seen in Fig. 5 and Table 3 shows the monthly forecast of energy for 2019-2028.

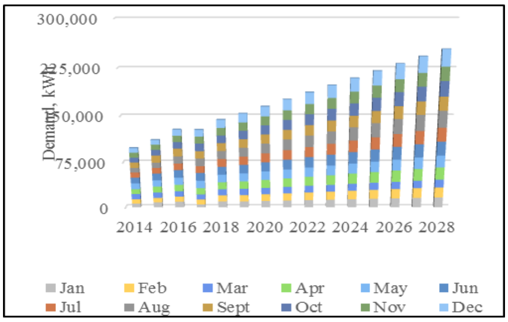

Fig. 5 CASURECO II Historical and Forecast Data

Table 3. Forecasted Monthly Electricity Consumption

CASURECO II Forecasted Demand (MWh) 2019 - 2028										
Yr / Mo.	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028
Jan	9,953	10,664	11,376	12,087	12,798	13,509	14,221	14,932	15,643	16,354
Feb	10,733	11,443	12,153	12,864	13,574	14,285	14,995	15,705	16,416	17,126
Mar	10,296	10,566	10,836	11,106	11,376	11,646	11,916	12,186	12,456	12,726
Apr	12,533	13,395	14,258	15,120	15,983	16,845	17,708	18,570	19,433	20,296
May	13,286	13,984	14,682	15,381	16,079	16,777	17,475	18,173	18,872	19,570
Jun	14,054	15,013	15,973	16,933	17,892	18,852	19,811	20,771	21,731	22,690
Jul	13,632	14,625	15,617	16,610	17,603	18,596	19,588	20,581	21,574	22,567
Aug	14,458	15,843	17,228	18,612	19,997	21,382	22,767	24,152	25,536	26,921
Sept	13,734	14,664	15,594	16,524	17,454	18,384	19,314	20,244	21,174	22,104
Oct	13,642	14,851	16,059	17,268	18,476	19,685	20,893	22,102	23,310	24,519
Nov	13,195	14,188	15,182	16,176	17,169	18,163	19,157	20,150	21,144	22,138
Dec	14,096	15,506	16,915	18,325	19,734	21,144	22,553	23,963	25,373	26,782

Z- Test

The two tailed Z- test validated the results in Table 3. The test result showed that there is no significant difference between the 2,000 samples of historical and forecasted data. The mean has relatively small difference. The Z- score is not in the 0.05 rejection region, thus, is not significant at the 5% level.

Table 4 Z-test Result

z-Test: Two Sample for Means		
	1012.401849	1016.192
Mean	1289.13753	1293.964
Known Variance	92168.82732	92860.3
Observations	2000	2000
Hypothesized Mean Difference	0	
z	-0.501814058	
P(Z<=z) one-tail	0.307899162	
z Critical one-tail	1.644853627	
P(Z<=z) two-tail	0.615798323	
z Critical two-tail	1.959963985	

Hierarchical Clustering

In this study, clustering commenced from the forecasted data. In the data selection, the author chose a month to consider (i.e. March 2019 in the Fig.6). The customers and their demand can be exported in Excel file through the export button.

March - April 2020
ISSN: 0193-4120 Page No. 4722 - 4734

Data selected will then be feed for clustering. MATLAB will generate a clustering tree once the cluster parameters are set in the GUI. To cut the tree, a variable cluster number will be set. Unlike in K- means clustering, there is no objective way to say the number of clusters in hierarchical clustering. Hierarchical clustering does not tell us how many clusters there are, or where to cut the dendrogram to form clusters. It is an explorative technique, different methods and parameters may be tried, then analyze the result.

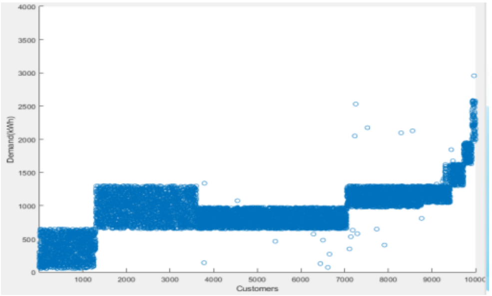

Fig. 6. Clustered Data by March 2019

The author set the number of clusters to maximum of 30 in Fig. 7. The nodes at the bottom identified the cluster order. The first node is cluster 22 mint green color, second node is cluster 8 apple green color, third node is cluster 7 ocean blue, cluster 18 apple green, cluster 10 yellow, and so on. There are 21 visible clusters in this case and 9 outliers in nodes 5, 6,13, 20, 23, 24, 28, 29 and 30. Outliers are those clusters with one or two individuals. The vertical axis indicates the distance between each cluster. Euclidian distance was the criterion for defining these clusters. In this case, the dissimilarity between the merged pair and the others will be the maximum of the pair of dissimilarities in each case. This sequence is repeated until the last clusters are joined; cutting of the tree was set according to the number of clusters. Furthermore, if the author wanted to cut the tree between 2500 and 3000, the cluster should be set to at least 4 and there will be no more outlier in this case.

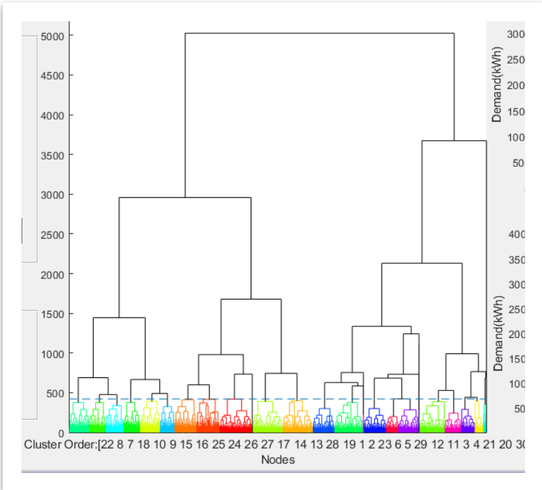

Fig. 7 Dendogram of 30 Clustered Customer

To picture the cluster, Fig. 8 shows the scatter plot of the 30 clustered customers while Fig. 9 is the selected cluster 1. This plot follows the sequence of clusters of clusters in the tree. The colors are just different. In this case, cluster 22 is powder blue, 12 is blue, 8 is sky blue, and 7 is yellow green and so on. However, the members of each cluster stayed the same. Fig. 11 shows the scatter plot of the selected cluster 1. Moreover, cluster 1are customers with more than 500 but less than 2000 kWh demand.

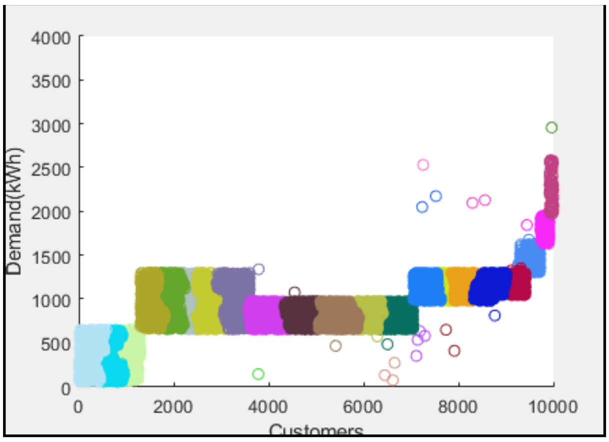

Fig. 8 Scattered plot of the 30 clusters

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March - April 2020
ISSN: 0193-4120 Page No. 4722 - 4734

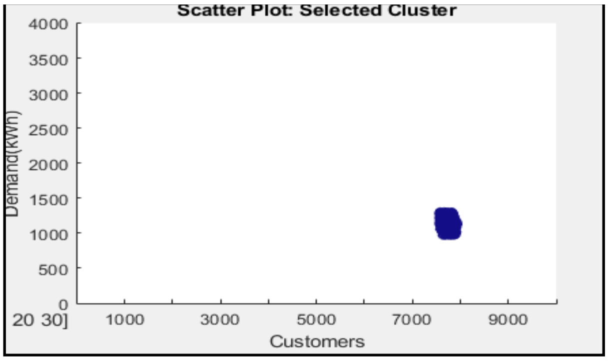

Fig. 9 Selected Cluster 9

Demand Response Program

The input for the DR program of residential customers are taken from the responses of the 500 random customers. The author divided the household appliances into lighting, refrigeration, kitchen appliances, laundry, recreation, heating and cooling, and miscellaneous (water pump, computer, curling or hair dryer, CCTV, vacuum and gadgets). The results showed that light bulbs, refrigerator, TV sets, electric fan, washing machine, flat iron, and electronic gadgets are the most common electricity consuming appliance of each consumer. Further, the author decided that washing machine and flat iron were the appliance that could be shifted with the least effect on the customer inconveniences. Two customers, labeled as Customer A and Customer B, is selected for their hourly consumption and will be subjected to the proposed load shifting mechanism.

Genetic Algorithm

To consider the convenience for the consumer, the author set the preferred time of shifting between 4:00 o'clock in the morning to 10 o'clock in the evening as time constraint. With this, most household are up and sleep at those time, respectively. Customer A uses washing machine from 6:00 o'clock to 8:00 o'clock in the evening from Monday to Friday while 8:00 o'clock to 12:00 noon during Saturdays and Sundays. Flat iron is use eight hours every Saturdays and Sundays from 8:00 o'clock to 5:00 o'clock in the afternoon. On the other hand, Customer B uses washing machine daily from 7:00 o'clock to 9:00 o'clock in the morning and flat iron from 7:00 o'clock to 12:00 noon Saturdays and Sundays. Both customers have almost the same usage of flat iron. Figure 3.10 shows that the customer A's washing machine shifted from the usual 6:00 o'clock to 8:00 o'clock evening to earlier time 4:00 o'clock to 6:00 o'clock in the evening. Further, Figure 3.11 show the usual use of flat iron from 8:00 o'clock to 6:00 o'clock in the evening shifted to5:00 o'clock to 3:00 o'clock in the afternoon. The loads are shifted by finding the best fit of time with low electricity cost through the Genetic Algorithm.

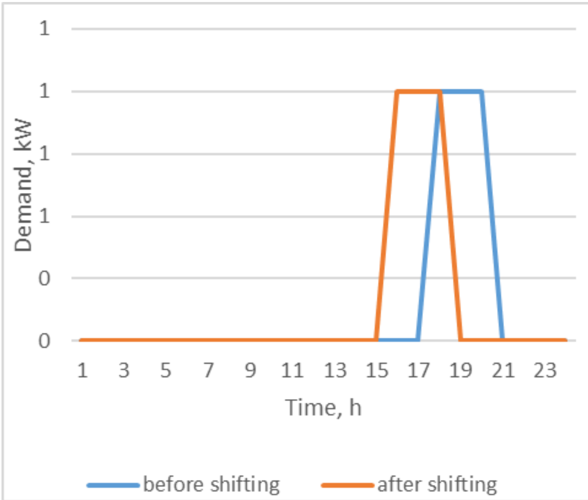

Fig. 10 Customer A Washing Machine Before and After Load Shifting.

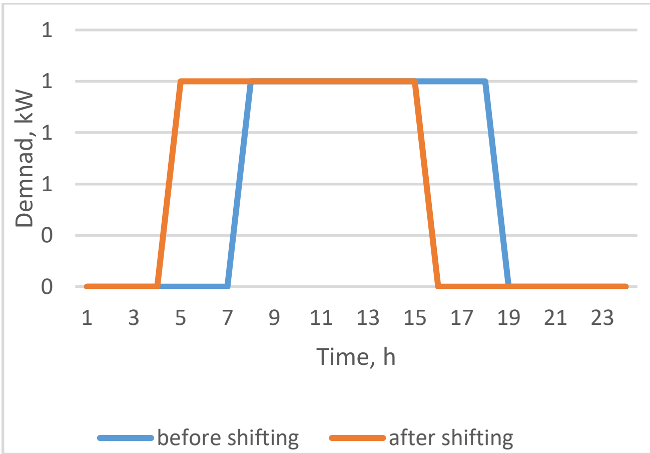

Fig. 11 Customer A Flat Iron Before and After Load Shifting.

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Cost Optimization

The energy consumption of customers for shiftable appliances are not only prices dependent but also on the costumer activities. It is important to know the customers energy behavior to optimize the prices for the next month. The cost optimization takes place while the GA finds best fit of the hourly price from the PEMC. The author used the Real Time Ex – Post price of PEMC for March 2019. Figure 3.12, Figure 3.13, Figure 3.14 and Figure 3.15 show the monthly electricity cost reduction of customers A and B before and after the loads are shifted. Table 3.5 showed the cost comparison of customers A and B before and after the load shifting. Customer A washing machine saves Php200.27 per month while customer B is Php57.17 after the loads are shifted. On the flat iron, customer A saves Php232.73 customer B saves Php67.66 both per month. Both customers save Php433 and Php124.81per month, respectively.

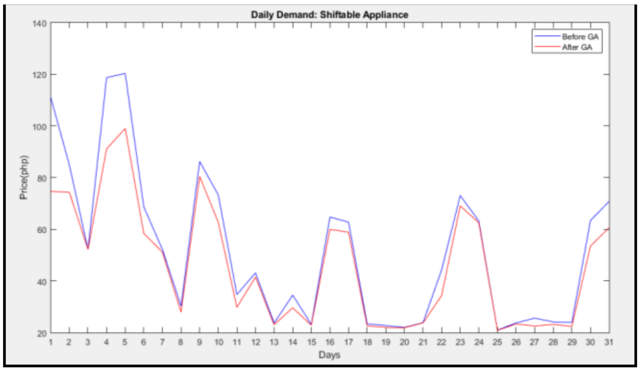

Fig. 12 Customer A Washing Machine Electricity Cost Reduction Before and After Load Shifting.

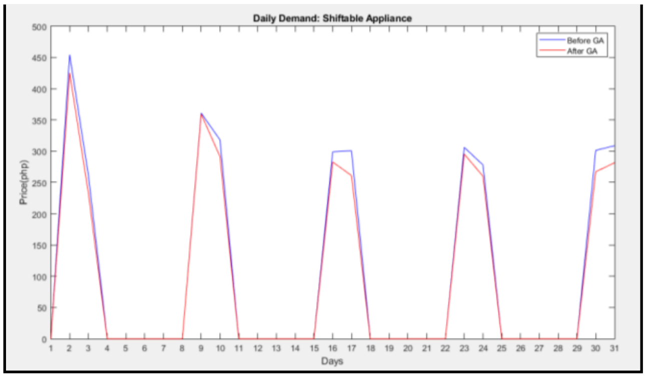

Fig. 13 Customer A Flat Iron Electricity Cost Reduction Before and After Load Shifting.

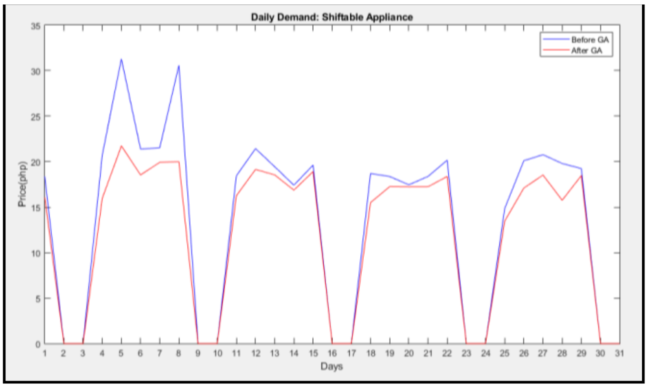

Fig. 14 Customer B Washing Machine Electricity Cost Before and After Load Shifting.

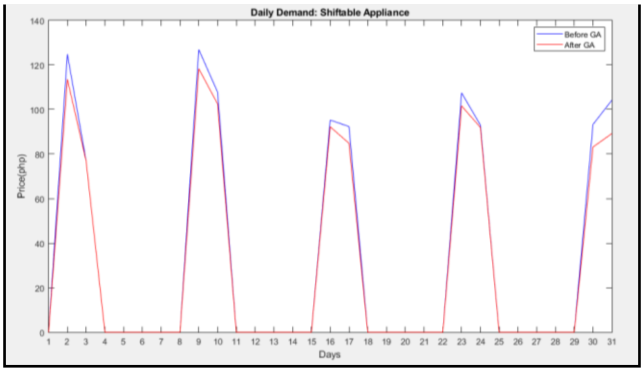

Fig. 15 Customer B Flat Iron Electricity Cost Before and After Load Shifting.

Table 5 Cost Comparison Before and After Load Shifting of Customer's Appliance

Customer	Before Load Shifting		After Load Shifting		Saving	
	Washing Machine	Flat Iron	Washing Machine	Flat Iron	Washing Machine	Flat Iron
A	1610.45	3189.15	1410.18	2956.42	200.27	232.73
B	427.93	1021.62	370.78	953.96	57.15	67.66

CONCLUSION

This paper presented a preliminary work of load shifting the residential customers' appliances during peak periods via Genetic Algorithm. The profiling of residential customers was the most tedious work for a local utility but will have greater impact once done. Moreover, the results of the hierarchical clustering is an advantage in grouping the customers according to their energy use. The results of the Weighted Least Square (WLS) showed that it is a

March - April 2020
ISSN: 0193-4120 Page No. 4722 - 4734

convenient tool to forecast future energy either monthly or hourly. The effects of the scheduling of the shiftable appliances during the peak hours through Genetic Algorithm displayed optimistic conclusion. Washing machine and flat iron are shifted by finding the best fit of time through the GA. The result though minimal energy saving for customers, indicated that all stakeholders will benefit once realized.

RECOMMENDATIONS

This study recommends incorporating the most convenient time for customer, the local energy retailers' economic benefits, real-time pricing of concerned utility, and scheduling of multiple shiftable household appliances. Moreover, an energy calculator can de designed to create awareness to the customers in their current habit and plan their future use. A design of a Home Energy Management System can be a dynamic support both for customers and the local utility.

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