Clustering-based Energy-aware Scheduling of Smart Residential Area

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Abstract—**Updating power system networks without changing the existing network facilities is done by modifying the consumer's energy demand curve using the Demand Response (DR) program. The increase in energy consumption, its environmental impact and limits in generation illustrates the importance of energy savings and alternate usage as Demand side management (DSM). Clustering methods provide proper planning and management of loads during the DR program. DR congestion of residential electrical loads scheduling is effectively managed by clustering of all the load curves in the smart residential area. The purpose of clustering the consumers is to understand the different energy behaviour better and identify the typical seasonal consumption patterns for the residential consumers, thereby creating a smart control strategy for the DR program. This work mainly focuses on applying load clustering method to reshape the load curve in the residential area during summer. The optimal scheduling of loads using this proposed method provide peak load management, Peak to Average Ratio (PAR) reduction, and the minimization of electricity cost of the consumer. The proposed seasonal clustering-based scheduling framework is solved using CPLEX solver.**

Index Terms—**clustering algorithms, energy management, load management, meter reading, smart grids.**

I. Introduction

An efficient energy management system needs to achieve the reliable operation of the power system. A smart grid (SG) is a system that interconnects the power system operation with information, communication, and control systems to improve the power system efficiency and reliability. Advanced smart technologies are used in SG to make the grid smart in two-way communication to exchange electricity data information between retailers and customers.

Residential Clustering techniques [1-3] are used to categorize daily load profiles from a large sample of customers over an entire year. Consumption schedule patterns result from clustering related to the behavioural changes of customers. The segregation can be used in different future studies, designing and managing loads during peak times [4]. In most research works, [5-8] clustering load profile is implemented and not well organized the clustering applications to DR analysis. The clustering-based residential demand side management aims to achieve peak load reduction and minimize the electricity bill considering consumer comfort [9] and [10]. Various clustering techniques are proposed in the previous papers for customers' electrical load segregation. In [11], the electrical consumption data of all residents' consumer and load curves are considered for the analysis. Adaptive K-means algorithm and hierarchical clustering are used for the load segmentation. High electrical consumption customers are the significant impact of creating peaks during peak hours. The K-means is the simplest, most straightforward method for handling and clustering large datasets efficiently. The limitation of this work is the consideration of an Electric Water heater (EWH) as the significant impact of peak load creation. This load alone is considered a shiftable load. In [12], a cumulative-based cluster approach is discussed for the analysis. They have analysed for a limited period over a day (evening peak period).

A probabilistic-based embedded clustering approach is discussed in [13]. The uncertainties of baseline demand at the residential level are analysed. The impact of the proposed method on cost-saving is not discussed. In [14], a two-stage K-means clustering algorithm is proposed to group the comfort sensitivity index by considering air conditioners as a shiftable load during the peak demand period. Spectral clustering is discussed for the load curve segmentation in [15]. The matrix perturbation method is used to find the K value in the proposed algorithm. In [16], a centroid-based clustering approach based on K-means is discussed to optimize biddings. This approach only applies to small-term economic strategies. A risk-based stochastic optimization with a clustering approach is used to perform DR applications in[17]. DR performance time duration is the main limitation of this work. In [18], a scenario-based Latin hypercube sampling algorithm is proposed by considering the pumped storage unit as a critical load during Off-peak hours. Also, the K-means clustering approach is used to minimize the number of scenarios. Epsilon constraint approach is proposed for solving the Pareto front decision-making method [19]. The minimizations of cost, the deviation between supply and demand, loss of load expectation are achieved in this approach. In [20], time drift issues are solved by Dynamic Time Warping (DTW) in load shape clustering. However, the computation time of DTW for the large dataset is more. By considering the aforementioned issues the clustering based optimal scheduling using DR strategies has been proposed in this work.

II. Clustering Framework

In this section, a clustering-based scheduling framework for the electricity consumption in a smart resident is proposed based on the ToU pricing scheme. Clustering of the residential DR load scheduling process is represented as a flow chart and is depicted in Fig.1. The residential usage data from each smart meter readings are used to cluster energy consumption behavioral demand [21]. Electricity Consumption profiles of all the residents are collected

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through an advanced metering infrastructure (AMI) system [22-23]. The pre-data processing provides cleaning the data and filling the missing data. In this paper, data processing is done for electricity consumption of seasonal variation for one year. After averaging and normalization of residential load profile, the k- means clustering is performed and is explained briefly in the following sections.

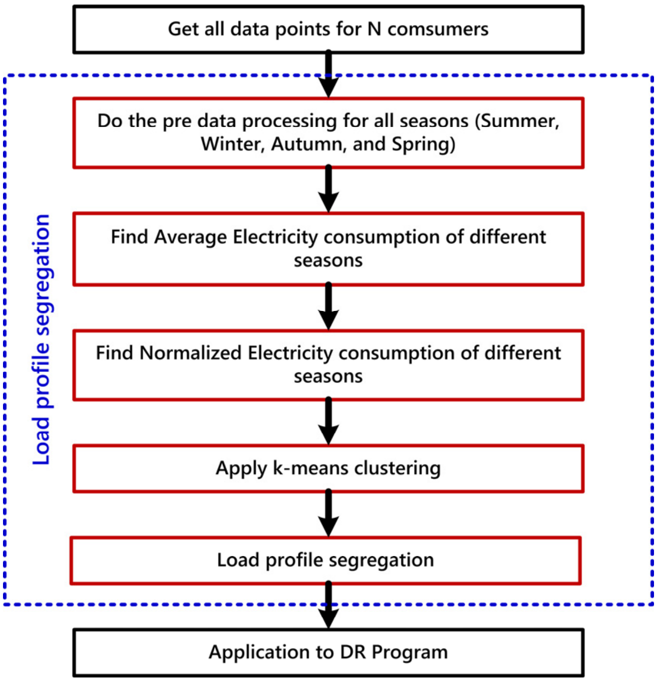


Figure 1. The flow chart of Residential load profile Clustering

The purpose of clustering the consumers is to understand the different energy behaviour better and identify the typical seasonal consumption patterns for the residential consumers and create a smart control strategy for the DR program [24-26]. Understanding such changes in a customer's seasonal behaviour can aid network operators in the longer-term planning of the power system networks based on the load monitoring system [27].

A. *The Dataset Used for Residential Customer Aggregation*

The dataset used in this approach is provided by National Renewable Energy Laboratory (NREL). The daily load curves of 200 residential customers of Midwest region of the United States as per RECS data set from January 1, 2018, to December 31, 2018, are used to aggregate the customers into the group. The electricity consumption of each consumer was recorded at 10 minutes intervals.

Seasons play a vital role in determining electricity consumption patterns. For example, in summer, residents with Air conditioners (AC) would consume a significantly higher amount of electricity at night compared to nights in winter. Due to seasonal variations, different peak demands occur to varying time-periods of the day.

This seasonal variation regarding the data is categorized into four seasons as. Summer: March, April, May, Autumn: September, October, November, Winter: December, January, February, Spring: June, July, August.

B. *K Means Algorithm*

The K-means algorithm is used for clustering time-series data. The objective of this approach is to obtain maximal intra-cluster and minimal inter-cluster similarity. Since the data is unlabeled, there is numerous method to group or cluster these data points into C = {C1, C2…Cn} clusters. Each approach has its own rule for finding the similarity among these data points (dp). K-means is a generic method of clustering based on minimizing Euclidian distance (ED) between the data points using equation (1).

$$\min_{Ci\in C} ED(C_i, dp)^2 \tag{1}$$

$$C_i = \frac{1}{S_{dp}} \sum_{dp_i \in S_{dp}} dp_i \tag{2}$$

The pseudo-code of this approach is shown in algorithm1. The trickiest step for this algorithm is to obtain the optimal number of clusters (K). The Elbow method is used in this approach, and it computes the Within cluster Sum of Squares (WSS). It is the sum of square of distances between the centroid and all the data points. It measures the clustering compactness that must be as small as possible.

The optimal number of clusters can be obtained as:

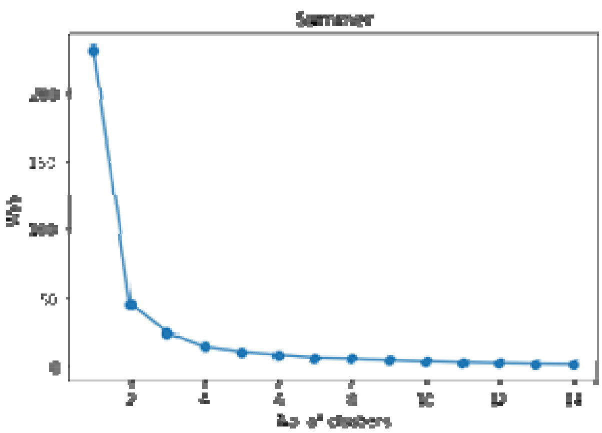
- First, compute K means clustering algorithm for different values of K (2<K<20);
- For each K, calculate WSS;
- Draw the graph for WSS vs K.

The knee point in the graph is an indicator of the number of clusters.

Algorithm 1:Pseudo code for K means clustering

Step1	:	Start the process by Get the data from the dataset. Determine the data point centroid randomly for the K samples
Step2	:	Compute (1) and find the closest centroids to each data point.
Step3	:	Assign each data into the nearest centroid.
Step4	:	Evaluate the mean of each cluster and find new centroid Ci (2)
Step5	:	Update the centers and Repeat the process until no changes occur.
Step6	:	Calculate WSS for all the clusters.

This proposed method considered different seasonal (summer, winter, autumn and spring) data frames of the Midwest region of the United States as per the RECS data set from January 1, 2018, to December 31, 2018. After running the K means clustering algorithm for different values of K (2<K<20), obtain the knee point for all the seasons.



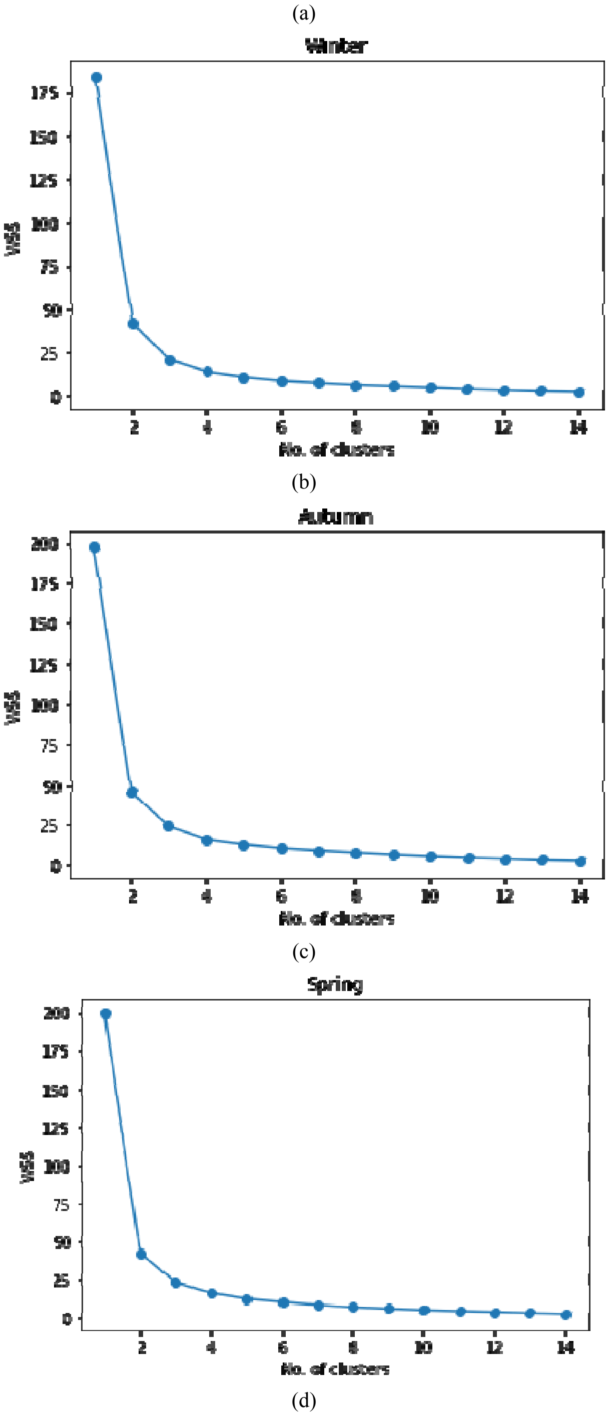


Figure 2. Elbow method for finding K value: a) Summer b) Winter c) Autumn d) Spring

From the Fig. 2 (a), it is identified that the knee point is 3 for summer. It represents the number of clusters (K) are 3 for the given dataset. The same value 3 is identified as knee point for the remaining season winter, autumn and spring are shown in Fig. 2 (b-d). So it is considered as the optimal number of clusters for all the seasons. This is the simplest way to obtain the value of K and is used to segregate the consumer's energy daily usage pattern. Higher values of K may create overfitting.

III. With and Without Clustering

In this paper, as the proposed approach deals with 200 residents, the load curve for each day is 200. We have calculated normalized average electricity consumption for each season (summer, winter, autumn and spring) for the analysis which is illustrated in Fig. 3 (a-d). Then K-means algorithm is used to cluster the 200 daily load curves into 3 clusters. The daily load curves of each group are normalized to get normalized average electricity consumption. For 365 days, 1095 average load curves are generated in total.

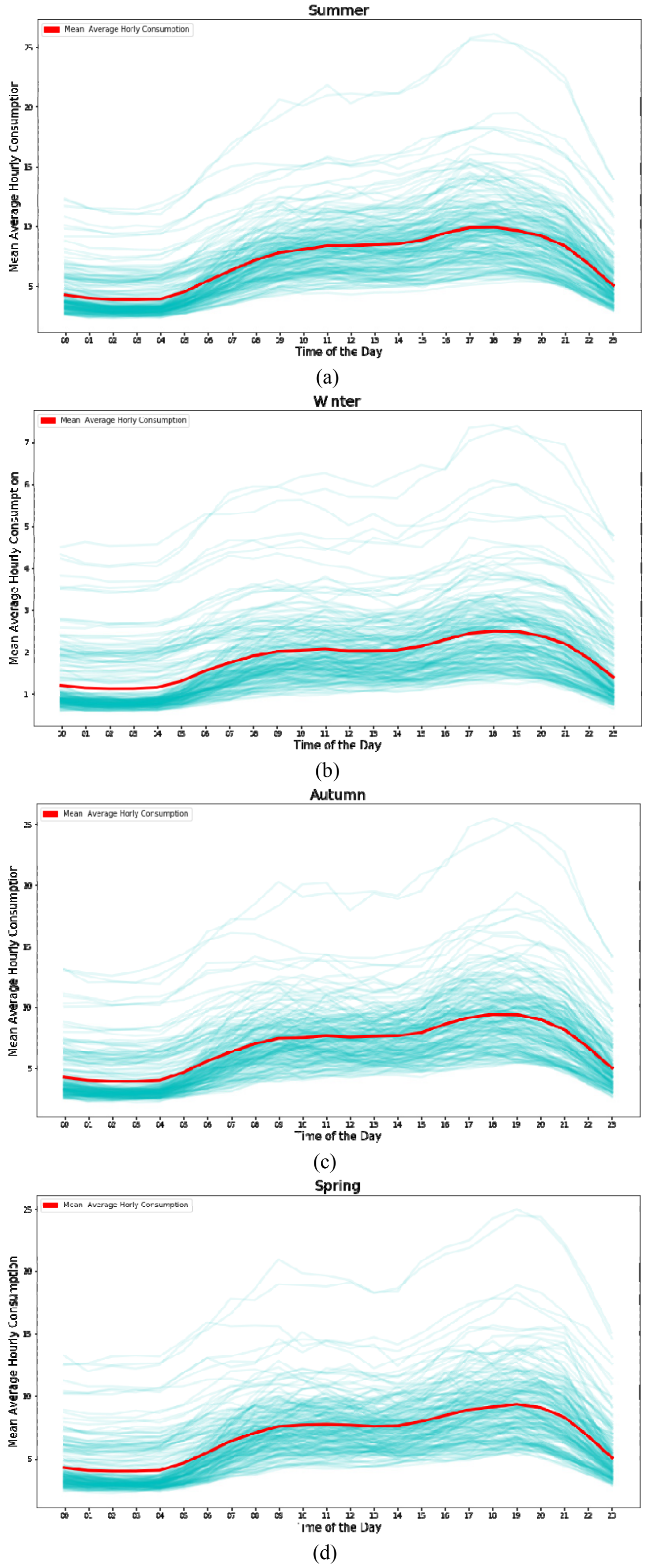


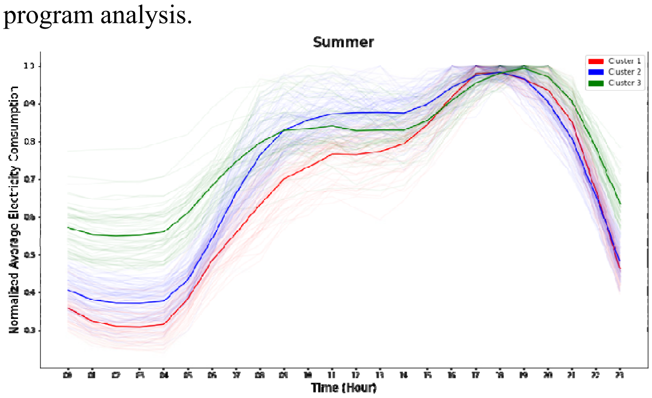
Figure 3. Average electricity consumption curve without clustering: a) Summer, b) Winter, c) Autumn, d) Spring

The result of clustering is illustrated as shown in Fig. 4. It represents the normalized average electricity consumption of different clusters, namely C1, C2, and C3, for all the seasons. The characteristics of seasonal variations are summarized as follows. From the graph, it is observed that peak power consumption occurs during evening time due to lighting and the availability of consumers using more appliances after return from work and less consumption during midnight because of sleep. The gradual increase of consumption around 6.00 in the morning is due to getting ready for office or school. From Fig. 4(a), the normalized average electricity consumption of cluster C1 is almost high throughout the day except from 1:00 to 5:00. This clustering data is taken for the application of DR analysis and is explained in the next section. Similarly, C3 has a slightly higher consumption than C2. Cluster C3 has minimal consumption than C1 and C2 from 12:00 to 15:00 due to the residents' unavailability. The higher peak occurs in the evening due to the use of Air conditioner. From Fig. 4(b), clusters C1 and C3 have two electricity consumption peaks, and C2 shows a stable curve throughout the day.

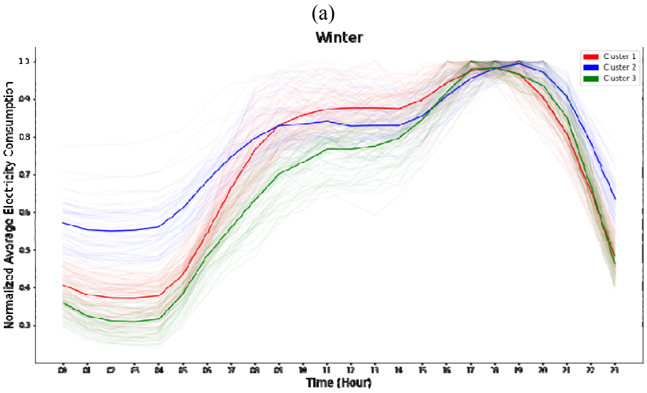
The steady curve is due to the usage of electric heaters by the consumer in C2.

From Fig.4(c) and 4(d), it is observed that the normalized average load curves are almost identical. In autumn season C1 and spring season C2 shows the stable load curve from 12:00 to 20:00 and other clusters showing two different peaks around 8:00 and 19:00.

These results are specific to the particular dataset which is collected from NREL. The purpose of clustering the consumers is to understand the different energy behaviour better and identify the typical seasonal consumption behaviour for the residential consumers, hence controlling their demand for the DR program. Based on the obtained results, it is recognized that consumers in clusters C1 are consuming more energy during peak hours in summer. In this work, we consider cluster C1 for the application of DR program analysis.



(a)



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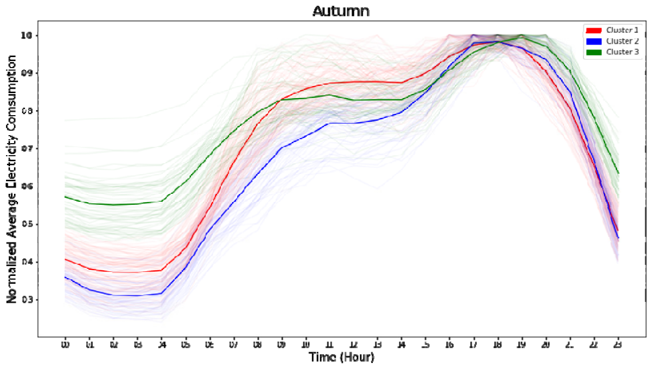

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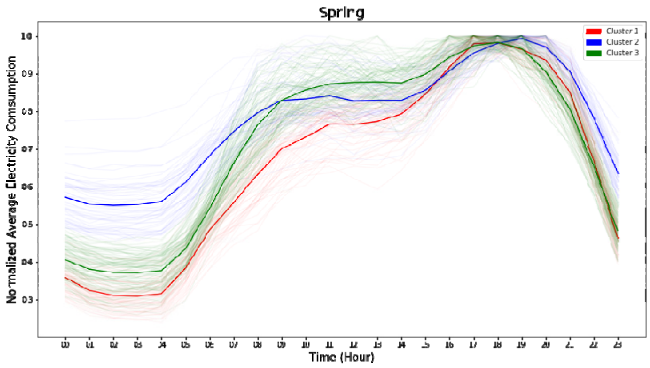


(d)

Figure 4. Seasonal Normalized Average Electricity consumption curve with clustering: a) Summer, b) Winter, c) Autumn, d) Spring

IV. Clustering Based DR Framework

The consumers might have different energy usage behaviour and willingness to take part in the DR program. For example, some consumers may prefer the minimization of electricity cost, and some may give importance to their comfort in the energy usage without bothering the electricity cost. By considering the above parameters, a clustering-based DSM scheduling program is proposed in this work.

A. Problem Formulation

Based on the seasonal clustering, we group the consumers into 3 clusters. The objective function is planned based on the benefit of utility and the consumers. High energy consumption customers are the significant impact of creating peaks during peak hours. So we have considered C1 data from summer analysis for the DR application. The scheduling optimization problem is planned by considering the following objective function and constraints. The minimization of the Clustering cost function is given in equation (3)

$$\min CF = w_1 EC + w_2 DC \tag{3}$$

where, w_1 and w_2 are the coefficients represent the degree of attention of customers' preference in cluster C on energy consumption cost and discomfort cost, respectively $w_1 + w_2 = 1$.

.Electricity consumption model

The electricity consumption cost function of each consumer is calculated using equations (4) and (5).

$$EC = \sum_{h=1}^{H} \sum_{r=1}^{R} ((E_{a,h}^{r} + \sum_{KA=1}^{N} E_{KA,h}^{r} S_{KA,h}^{r}) P_e)\Delta h \tag{4}$$

$$S_{KA,h}^{r} = \begin{cases} 0, ApplianceOFF \\ 1, ApplianceON \end{cases} \tag{5}$$

Discomfort cost model

The discomfort cost model for each consumer is expressed as below in equation (6). It is the measure of inconvenience faced by the customers between the permission given by the utility to operate the appliances for the operation of the requested appliance.

$$DC = \sum_{h=1}^{H}\sum_{a=1}^{N}\sum_{r=1}^{R}\left|\frac{KA_r - RA_{r.h}}{KA_r - AA_{r.h}}\right|^2 P_e \Delta h \tag{6}$$

B. *Operational Constraints*

The operational constraints of appliances are given in the following equations. During the DR program, the number of controllable appliances should be greater than zero as per equation (7).

The variation between the consumption before and after scheduling ensures the consumer's satisfaction. The appliance must operate ON-period and is given in equation (8). Where, are the starting and ending time of controllable appliances and the time duration for the working appliance as in equation (9) needed to finish the operation of controllable appliances in resident 'r'. Equation (10) defines the appliance's energy consumption limit. This formulation ensures that controllable appliance demand does not exceed the maximum capacity of utility at hour 'h'.

$$KA_r > 0 \tag{7}$$

$$\sum_{r=1}^{R}\sum_{h=S_k}^{e_k} S_{KA,h}^{r} = D_{KA}^{r}, \forall KA \tag{8}$$

$$D_{KA}^{r} \le (e_k - s_k) \tag{9}$$

$$0 \le E_{KA,h} \le E_{KA,\max} \tag{10}$$

Consumers can change their energy profile management by shifting their peak loads to OFF peak. This method improves the participation of the residential customers with non-shiftable loads in the DR program.

V. Simulation Results

This model is planned as a mixed-integer nonlinear (MINLP) optimization problem. This MILNP problem from equation (2)-(10) is solved using CPLEX optimization solver using YALMIP and MATLAB interface. CPLEX efficiently solves the linear and nonlinear optimization problem with an objective function of cost and peak load minimization by considering user preferences.

Table I show the responsive loads for shifting and non-shiftable loads ratings and working duration of a single summer cluster. Various schemes and the parameter settings are given in Table II. Simulation results are discussed here for analyzing the performance of the proposed method for various considerable parameters.

The electricity consumption curve of different schemes is presented in Fig. 5. The influence of the parameters of cost and comfort on the performance of the proposed method under different schemes is discussed in this section. For this analysis, the residential data of cluster1 during summer is considered. Thus consumers in C1 consume more energy when compared to other clusters in that season. Concerning the proposed method, there is a considerable reduction of the cluster's PAR and electricity consumption cost by shifting the peak load to OFF-peak periods.

Simulation results show the impact of the parameters, cost, and comfort on the performance of the proposed method. Comparison between different schemes for the fundamental characteristics of energy consumption cost and PAR are shown in Table III. From that, it is implied that considerable reduction of PAR and energy consumption cost of the cluster for all the schemes.

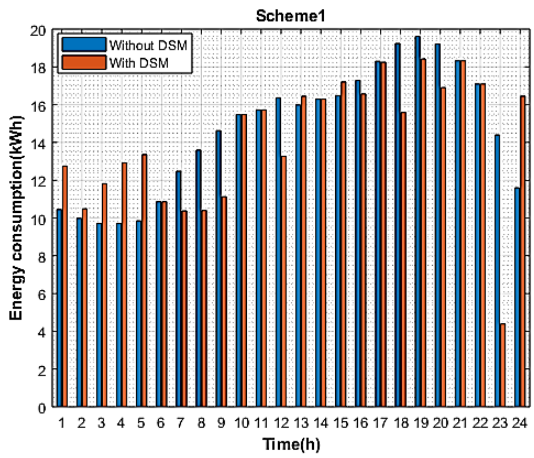
It is identified that in scheme 1, consumers are only bothered about the electricity consumption cost and without worrying about comfort. Therefore, it results in the lowest PAR and cost by the proper shifting of peak loads. Different size peaks occur at different periods of the day, depending on the season. In this approach, we considered only the summer clusters for the DR application. In the future, the same methodology can be applied to the remaining seasons.

TABLE I. APPLIANCES RATINGS AND SHIFTING FLEXIBILITY FONTS

Appliances	Rated power (kW)	Operating time	Shifting Flexibility (Hrs.)
Controllable Loads			
Water heater	3.1	6.00 A.M - 7.00 A.M	1-2
Cloth dryer	1.4	11.00 A.M - 12.00	1-3
Dish washer	1.32	13.00 P.M - 14.00 P.M	1-3
Coffee maker	0.8	18.00 P.M - 19.00 P.M	1-2
Toaster	1.1	9.00 P.M - 10.00 P.M	1-2
Air conditioner	1.14	21.00 P.M - 2.00 A.M	1-2
Electric vehicle	3.6	21.00 P.M - 23.00P.M	1-2
Electric stove	0.2	12.00 - 13.00 P.M	1-2
Oven	1.3	8.00 A.M - 9.00 A.M 18.00 P.M - 19.00 P.M	1-2
Hair Dryer	1.5	7.00 A.M - 8.00 A.M	1-2
Iron	1.0	19.00 P.M - 20.00 P.M	3-5
Vacuum Cleaner	0.4	11.00 A.M - 12.00	1-3
Pool pump	0.9	21.00 P.M - 22.00 P.M	1-2
Washing machine	0.85	11.00 A.M - 12.00	1-2
Uncontrollable Loads			
Lighting	0.2	-	-
TV	0.08	-	-
Refrigerator	1.66	-	-

TABLE II. VARIOUS SCHEMES AND PARAMETER SETTINGS

Scheme	Parameter settings	
	w_1	w_2
Scheme 1	1	0
Scheme 2	0.5	0.5
Scheme 3	0	1



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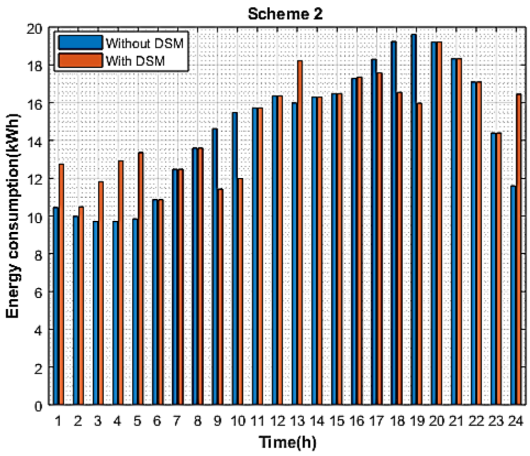

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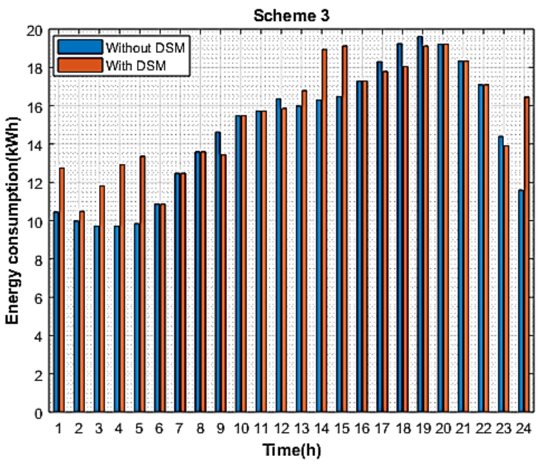

(c)

Figure 5. Normalized Energy consumption curve with and without DSM: a) schemes 1; b) schemes 2 and c) schemes 3

The proposed method reduces the PAR by 29.44 % from 1.0881 to 0.7678 and electricity consumption cost by 20.78% from 7.2587$ to 5.7501$. Compared to without DSM, the proposed schemes perform better.

The scheme1 results are better for the parameter as they have for the cost reduction. Compare to scheme 2, and it reduces the PAR by 4.07% and cost by 5.38%. Compare to scheme 3, and it reduces the PAR by 16.11% and cost by 9.47%.

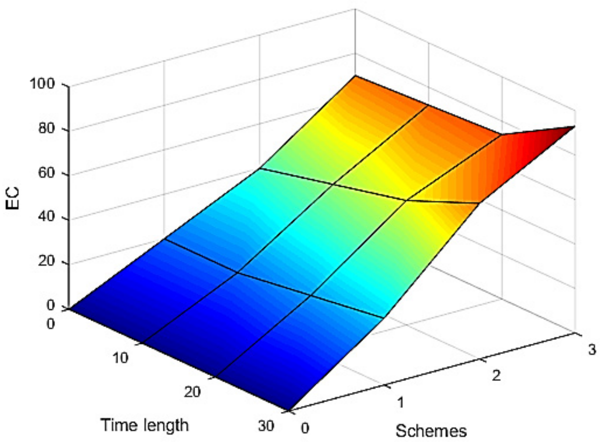

Figure 6. Energy consumption Cost (EC) for various schemes

The results show that PAR and consumer comfort are conducive to shifting the peak loads and reducing the consumer's electricity consumption costs.

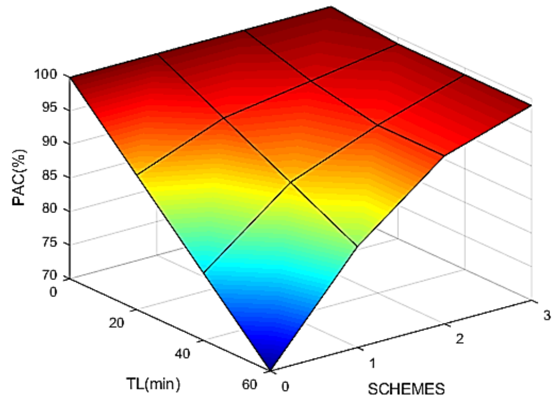

Figure 7. Percentage Average Comfort (PAC) for various schemes

The electricity consumption costs (EC) of different schemes are presented in Fig. 6. High EC occurs in scheme 3 because of their preference is given for comfort and not willing to shift their load during peak hours.

TABLE III. REDUCTION OF PAR AND ENERGY CONSUMPTION COST FOR VARIOUS SCHEMES

Approach	PAR	PAR reduction (%)	Average EC ($)	EC Reduction (%)
Without DSM	1.0881	0	7.2587	0
Scheme 1	0.7678	29.4366	5.7501	20.7833
Scheme 2	0.8004	26.4406	6.0772	16.2770
Scheme 3	0.9153	15.8808	6.3518	12.4939

Percentage Average Comfort (PAC) of different schemes are presented in Fig.7 and less comfort is identified in scheme 1 due to their compromise to shift the loads.TL is the time length for performing the DR schemes. The optimal scheduling of loads using this clustering-based optimization method benefit both utilities and consumers using peak load management, PAR reduction, and the minimization of electricity cost of the consumer. If their preference towards cost reduction means better go for scheme1. If their preference is on comfort means scheme3 and those who are bothered about cost as well as comfort can choose scheme 2. In this method, the consumer can adopt any proposed scheme based on either cost-oriented or comfort-oriented willingness.

VI. CONCLUSION

In this paper, clustering-based scheduling of smart residential areas was proposed to cluster the load profiles and efficiently schedule them to reduce PAR and electricity consumption cost of cluster. Also, the seasonal variations have been analyzed. It describes a seasonal clustering strategy that can be used in residential DSM programs.

This proposed method of load profiling identifies the peak period users during summer and applies the technique of DR for shifting the energy usage profile to manage the peak demand. The simulation results show that the performance of the proposed method for various considerable parameters and different schemes.

The influence of the parameters of cost and comfort on the performance under different strategies is discussed. It shows that the consumer's consumption cost could reduce by around 21%, and the PAR could reduce by approximately 29% for scheme 1. The consumer can adopt any proposed scheme based on either cost or comfort-oriented willingness.

NOMENCLATURE

H	Total number of time period
N	Total number of appliances
R	Total number of residents
EC	Electricity consumption Cost
DC	Discomfort Cost
CF	Combined cost function of EC and DC
KA	Controllable Appliances
C_i	Centroids of clusters
$AA_{r,h}$	Number of allowed controllable appliances to turn ON in resident 'r' at time 'h'
D^r_{KA}	Operating duration of controllable appliances in resident 'r'
$E^r_{a,h}$	Energy consumption of uncontrollable appliances in resident 'r'
$E_{KA,h}$	Energy consumption of controllable appliances in resident 'r'
$E_{KA,max}$	Maximum energy consumption of controllable appliances
KA_r	Total number of controllable appliances in resident 'r'
$RA_{r,h}$	Number of requested controllable appliances in resident 'r' at time 'h'
Δh	Length of time-period
P_e	Time of use electricity price in time h
S_{dp}	Set of consumer data points
$S_{a,h}$	Status of each appliance at time h
e_k	Ending time of appliance to finish the operation
S_k	Starting time of the controllable appliance

REFERENCES

[1] T. Teeraratkul, D. O'Neill, and S. Lall, "Shape-based approach to household electric load curve clustering and prediction," IEEE Trans. Smart Grid, vol. 9, no. 5, pp. 5196–5206, Sep. 2018, doi:10.1109/TSG.2017.2683461

[2] S. Dasgupta, A. Srivastava, J. Cordova, and R. Arghandeh, "Clustering household electrical load profiles using elastic shape analysis," in 2019 IEEE Milan PowerTech, Milan, Italy, Jun. 2019, pp. 1–6. doi:10.1109/PTC.2019.8810883

[3] G. Le Ray and P. Pinson, "Online adaptive clustering algorithm for load profiling," Sustain. Energy Grids Netw., vol. 17, p. 100181, Mar. 2019. doi:10.1016/j.segan.2018.100181

[4] M. Sun, Y. Wang, G. Strbac, and C. Kang, "Probabilistic peak load estimation in smart cities using smart meter data," IEEE Trans. Ind. Electron., vol. 66, no. 2, pp. 1608–1618, Feb. 2019. doi:10.1109/TIE.2018.2803732

[5] S. Mohammad Hoseini Mirzaei, B. Ganji, and S. Abbas Taher, "Performance improvement of distribution networks using the demand response resources," IET Gener. Transm. Distrib., vol. 13, no. 18, pp. 4171–4179, Sep. 2019. doi:10.1049/iet-gtd.2018.6616

[6] A. Malik, N. Haghdadi, I. MacGill, and J. Ravishankar, "Appliance level data analysis of summer demand reduction potential from residential air conditioner control," Appl. Energy, vol. 235, pp. 776–785, Feb. 2019. doi:10.1016/j.apenergy.2018.11.010

[7] T. Li and M. Dong, "Real-time residential-side joint energy storage management and load scheduling with renewable integration," IEEE Trans. Smart Grid, vol. 9, no. 1, pp. 283–298, Jan. 2018. doi:10.1109/TSG.2016.2550500

[8] B. Najafi, S. Moaveninejad, and F. Rinaldi, "Data analytics for energy disaggregation: Methods and applications," in Big Data Application in Power Systems, Elsevier, 2018, pp. 377–408. doi:10.1016/B978-0-12-811968-6.00017-6

[9] Y. Wang et al., "Energy management of smart micro-grid with response loads and distributed generation considering demand response," J. Clean. Prod., vol. 197, pp. 1069–1083, Oct. 2018. doi:10.1016/j.jclepro.2018.06.271

[10] S. Nan, M. Zhou, and G. Li, "Optimal residential community demand response scheduling in smart grid," Appl. Energy, vol. 210, pp. 1280–1289, Jan. 2018. doi:10.1016/j.apenergy.2017.06.066

[11] M. A. Z. Alvarez, K. Agbossou, A. Cardenas, S. Kelouwani, and L. Boulon, "Demand response strategy applied to residential electric water heaters using dynamic programming and K-means clustering," IEEE Trans. Sustain. Energy, vol. 11, no. 1, pp. 524–533, Jan. 2020. doi:10.1109/TSTE.2019.2897288

[12] A. Satre-Meloy, M. Diakonova, and P. Grünewald, "Cluster analysis and prediction of residential peak demand profiles using occupant activity data," Appl. Energy, vol. 260, p. 114246, Feb. 2020. doi:10.1016/j.apenergy.2019.114246

[13] M. Sun, Y. Wang, F. Teng, Y. Ye, G. Strbac, and C. Kang, "Clustering-based residential baseline estimation: A probabilistic perspective," IEEE Trans. Smart Grid, vol. 10, no. 6, pp. 6014–6028, Nov. 2019. doi:10.1109/TSG.2019.2895333

[14] L. Chen, Y. Yang, and Q. Xu, "A two-stage control strategy of large-scale residential air conditionings considering comfort sensitivity of differentiated population," IEEE Access, vol. 7, pp. 126344–126354, 2019. doi:10.1109/ACCESS.2019.2937358

[15] S. Lin, F. Li, E. Tian, Y. Fu, and D. Li, "Clustering load profiles for demand response applications," IEEE Trans. Smart Grid, vol. 10, no. 2, pp. 1599–1607, Mar. 2019. doi:10.1109/TSG.2017.2773573

[16] J. Iria and F. Soares, "A cluster-based optimization approach to support the participation of an aggregator of a larger number of prosumers in the day-ahead energy market," Electr. Power Syst. Res., vol. 168, pp. 324–335, Mar. 2019. doi:10.1016/j.epsr.2018.11.022

[17] M. Brolin and C. Sandels, "Controlling a retailer's short□term financial risk exposure using demand response," IET Gener. Transm. Distrib., vol. 13, no. 22, pp. 5160–5170, Nov. 2019. doi:10.1049/iet-gtd.2018.6708

[18] Y. Ma, C. Li, J. Zhou, and Y. Zhang, "Comprehensive stochastic optimal scheduling in residential micro energy grid considering pumped-storage unit and demand response," J. Energy Storage, vol. 32, p. 101968, Dec. 2020. doi:10.1016/j.est.2020.101968

[19] H. Chamandoust, G. Derakhshan, S. M. Hakimi, and S. Bahramara, "Tri-objective scheduling of residential smart electrical distribution grids with optimal joint of responsive loads with renewable energy sources," J. Energy Storage, vol. 27, p. 101112, Feb. 2020. doi:10.1016/j.est.2019.101112

[20] E. Azizi, A. M. Shotorbani, M.-T. Hamidi-Beheshti, B. Mohammadi-Ivatloo, and S. Bolouki, "Residential household non-intrusive load monitoring via smart event-based optimization," IEEE Trans. Consum. Electron., vol. 66, no. 3, pp. 233–241, Aug. 2020. doi:10.1109/TCE.2020.3008261

[21] F. Wang, K. Li, C. Liu, Z. Mi, M. Shafie-Khah, and J. P. S. Catalao, "Synchronous Pattern Matching Principle-Based Residential Demand Response Baseline Estimation: Mechanism analysis and approach description," IEEE Trans. Smart Grid, vol. 9, no. 6, pp. 6972–6985, Nov. 2018. doi:10.1109/TSG.2018.2824842

[22] F. Elghitani and W. Zhuang, "Aggregating a large number of residential appliances for demand response applications," IEEE Trans. Smart Grid, vol. 9, no. 5, pp. 5092–5100, Sep. 2018. doi:10.1109/TSG.2017.2679702

[23] L. Zhao, Z. Yang, and W.-J. Lee, "The impact of Time-of-Use (TOU) rate structure on consumption patterns of the residential customers," IEEE Trans. Ind. Appl., vol. 53, no. 6, pp. 5130–5138, Nov. 2017. doi:10.1109/TIA.2017.2734039

[24] A. Al-Wakeel, J. Wu, and N. Jenkins, "K-means based load estimation of domestic smart meter measurements," Appl. Energy, vol. 194, pp. 333–342, May 2017. doi:10.1016/j.apenergy.2016.06.046

[25] S. Haben, C. Singleton, and P. Grindrod, "Analysis and clustering of residential customers energy behavioral demand using smart meter data," IEEE Trans. Smart Grid, vol. 7, no. 1, pp. 136–144, Jan. 2016. doi:10.1109/TSG.2015.2409786

[26] J. Thakur and B. Chakraborty, "Demand side management in developing nations: A mitigating tool for energy imbalance and peak load management," Energy, vol. 114, pp. 895–912, Nov. 2016. doi:10.1016/j.energy.2016.08.030

[27] F. Luo, G. Ranzi, W. Kong, G. Liang, and Z. Y. Dong, "Personalized residential energy usage recommendation system based on load monitoring and collaborative filtering," IEEE Trans. Ind. Inform., vol. 17, no. 2, pp. 1253–1262, Feb. 2021. doi:10.1109/TII.2020.2983212