# Efficient management of demand in a power distribution system with smart meter data

Khan, Zafar; Jayaweera, Dilan

*DOI:*
10.1109/PTC.2019.8810908



*Citation for published version (Harvard):*
Khan, Z & Jayaweera, D 2019, Efficient management of demand in a power distribution system with smart meter data. in *2019 IEEE Milano Powertech.*, 8810908, Power Tech Conference, Institute of Electrical and Electronics Engineers (IEEE), IEEE PowerTech 2019, 13th, Milano, Italy, 23/06/19. https://doi.org/10.1109/PTC.2019.8810908

# Efficient Management of Demand in a Power Distribution System with Smart Meter Data

Zafar A. Khan, *Student member IEEE*, Dilan Jayaweera, *SeniorMember IEEE*

Department of Electronics, Electical and Systems Engineering

University of Birmingham, U.K.

***Abstract*— Smart power distribution systems require adopting smart approaches for the maximization of benefits. This paper presents a novel approach for demand side management (DSM) in a power distribution system by incorporating smart meter data. The approach is aimed at savings maximization by minimizing the energy consumption cost of electricity consumers. The core of the approach consists of data clustering in order to forecast demand for the benefit of DSM decisions by incorporating alternate profiles through extended k-means algorithm, Taylor series linearization and particle swarm optimization. Two cases including integration of PV generation are simulated using the Irish data of more than 5000 smart meters considering different demand flexibility levels in different Scenarios. PV profiles are generated using historical weather data. In both cases, the results demonstrate that the proposed DSM approach is more beneficial than conventional DSM approach. The paper argues that inherent non-linearity of raw profiles, is likely to provide suboptimal DSM solutions against electricity consumer cost savings, however the uniformity and smoothness of reshaped alternate profiles are more likely to provide optimal DSM solutions, providing electricity consumers a true benefit for their participation in the DSM process.**

***Keywords*— *demand side management, load forecasting, load profiling, smart meter data***

## I. INTRODUCTION

Demand side management (DSM) is one of the smart techniques that enable smart grids to achieve their intended functionality [1]. A great deal of benefit in terms of reduction of peak of load and reshaping the electricity demand can be achieved by managing the energy demand at consumers end [2]. Efficient DSM can potentially optimize the utilization of existing infrastructure which can help in delaying construction of infrastructure for generation, transmission or distribution networks [3].

Underlying principle behind the implementation of DSM within the context of smart grids is to improve the efficiency, security, reliability and sustainability of the system by enabling the renewable energy sources (RES) integration into the system while utilizing the maximum capacity of the existing infrastructure [3, 4]. Literature shows that the primary objective of the DSM is to reduce system peak load and operational cost [3]. Due to its effectiveness, load shifting [5] is most commonly used and widely applied load management technique in current distribution networks [3]. This technique shifts the load from peak hours to off-peak hours by benefiting from the time independence of the load. Implementation of such a technique requires prior knowledge about the expected load profile of the consumer and sophisticated coordination between the electricity consumer and utility.

DSM can potentially benefit the entire smart grid, but the benefits are more apparent at the distribution network level [3]. Although the latent demand flexibility at the consumer end can be exploited using DSM, for a distribution network with thousands of consumers, managing the demand at the individual consumer level is a challenging task. Alternatively, aggregation of load at the substation level can potentially blind the operator from the load variations at a lower level. Thus, the demand flexibility at individual consumer level should be exploited using smart meter data. However, size of smart meter data, high dimensionality and heterogeneity of the load profiles [6] poses great computational challenges to the application of DSM at the electricity consumer level.

The size and heterogeneity of the profiles can be managed using appropriate computational techniques like data mining algorithms. Data clustering is one such technique which tends to construct clusters with characteristics such that the profiles within the same clusters are relatively similar and profiles of different clusters are relatively different [6]. Many clustering techniques have been used in the literature for clustering the smart meter data, and k-means clustering algorithm [7] is one of the most commonly used clustering algorithm. Different variations of the k-means clustering have also been reported in literature including fuzzy c-means [8], x-means clustering [9] etc. However, authors of [6] are of the view that the number of partitions/clusters is governed by the local criterion of similarity. This essentially refers to the fact that type of the data and different data features such as load patterns, determine the number of clusters which can then be used to generate representative profiles.

Clustering load profiles reduces the number of individual load profiles, however, the high dimensionality and non-linear nature of energy consumption patterns undermines implementation of linear optimization techniques for DSM. At the same time load is stochastic and depends on a multitude of external factors. The non-linear interaction of the load with these factors adds to the complexity in load forecasting which is a pre-requisite for effective implementation of DSM [10, 11].

This paper presents an innovative DSM approach that can be employed in the future smart grids. The approach uses smart meter data for extended k-means clustering and profiling to develop alternate profiles. The alternate profiles transpose the N-dimensional non-linear functions into a concatenation of continuous differentiable linear functions. These profiles are incorporated to generate load forecast and DSM application. The effect of prosumer has also been studied by considering 10% penetration of solar PV generation. The contribution of the approach originates from the combination of the extended k-mean clustering, alternate profiling for use in forecasting, cluster selection index and DSM application at cluster level.

## II. METHODOLOGY

The methodology for the DSM approach consists of multiple stages including data clustering, alternate load profiling [12], load forecasting, cluster selection and load shifting by DSM. A special consideration has been given to integration of renewable energy source i.e. solar photovoltaic (PV) by incorporating the PV capacity of 10% of individual clusters. The procedure adopted for all stages is detailed below.

### A. *Smart meter data clustering*

As the number of consumers increases, the amount of data generated by smart meters tends to increase exponentially. The size of the data is a major hurdle in effective utilization of the smart meter data. The big data of smart meters requires machine learning algorithms and data mining techniques to extract the hidden knowledge and find patterns in the data which can be useful for system studies at different hierarchical level of the power system [10]. Data clustering is an unsupervised learning technique, which can potentially group smart meter consumers with similar consumption patterns [10]. There are many clustering algorithms which are used for clustering the smart meter data, however, k-means clustering is one of the most widely used clustering algorithm due to its simplest principle and fast convergence speed [13].

A modified form of k-means clustering, namely extended k-means clustering, is proposed in our early research [12], which is used in the study of this paper. The detailed steps of the algorithm are given in Table I [12].

The first stopping criterion of the extended k-means clustering algorithm pertains to a minimum number of consumers in the cluster and second criterion refers to the reduction in intra-cluster pattern similarity. The extended k-means clustering produces distinctive clusters with high intra-cluster pattern similarity. The resultant clusters are then used for the extraction of load profiles for development of alternate profiles.

### B. *Alternate load profiling*

The final clusters are used to extract a representative profile for each cluster. The resulting raw profiles are often considered as the final representative profiles for the cluster. However, to develop the alternate profiles, the raw profiles are smoothed and then systematically linearized around the energy threshold points using Taylor series linearization process [12]. The alternate linearized profiles are optimized to enhance accuracy of representation by incorporating weighting factors for each individual pattern (linear pattern) in the profiles. These weighting factors are determined using particle swarm optimization with an objective function to minimize the difference of energy, between raw and alternate profiles, consumed during the interval of each pattern. Thus, N-dimensional raw profiles are linearized into concatenation of linear functions. The detailed process of linearization is given in Fig. 1 [12].

### C. *Load forecasting*

The smart meter data provides an opportunity to forecast the load at different hierarchical system levels, however, the smaller the system, the more the uncertainty which is challenging. This has a direct impact on forecasting and alternate profiles can benefit the forecasting process by increasing the forecast accuracy and processing speed.

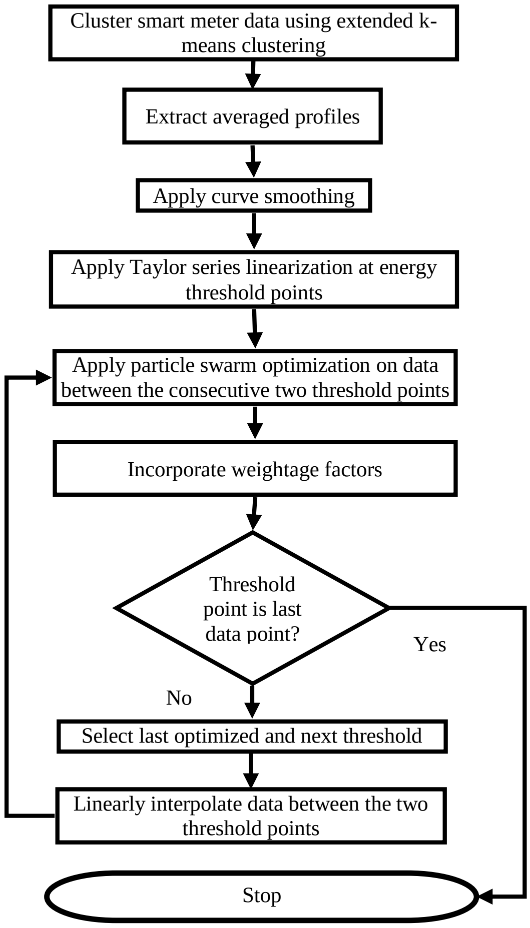



Fig. 1. Alternate profile generation process

Artificial neural networks (ANNs) are commonly used in modern research for load forecasting [14]. The neural network architecture is set as feed-forward neural network with 4 layers and each consisting of 6 neurons. The prediction variables used in this study include temperature as the weather variable and hour of the day as calendar variable. Finally, the load variables included 24 hours lagged load, load at same hour from the previous week and average load

TABLE I
**ALGORITHM** : EXTENDED K-MEANS CLUSTERING

1: Let k=2. Initialize the k-means clustering with 2 clusters
2: Check stopping criterion 1 for cluster of child node 1
3: If stopping criterion 1 is true, save the cluster as output cluster and break the cluster out of loop
4: If false, check stopping criterion 2
5: If stopping criterion 2 is true, save the node of cluster which resulted in cluster satisfying criterion 2 as output cluster and break the cluster out of loop
6: If false, go to step 7
7: Repeat steps 2-5 on remaining cluster child node clusters
8: If stopping criteria 1 & 2 are false, apply k-means clustering with k=2 on all the child nodes/clusters
where the stopping criteria 1 & 2 are false
9: Repeat the steps 2-5 on all nodes of child clusters
10: Repeat the steps 2-8 at each stage until criteria 1 & 2 are true for all clusters
11: Save all the output clusters as final clusters

of previous 24 hours. The same architecture and variable were used to forecast for both raw and alternate profiles. Training data used for both raw and alternate profiles is half hourly energy consumption records of 504 days and the forecast was generated for the next 168 hours.

An important aspect of the forecast accuracy using a neural network is determining the correct learning rate. The convergence of solution is highly dependent on learning rate [15] and this necessitates a suitable learning rate for good forecast results. The best learning rate for raw and alternate profile may vary as the data functions vary significantly from each other. To address this issue, a dynamic algorithm is created which starts training the network for each raw and alternate profile with initial learning rate of 0.01 and increment of 0.01 up till 1. The algorithm selects the learning rate which gives minimum forecasting error. The dynamic selection of learning rate enables higher forecasting accuracy as each profile has optimum accuracy at different learning rate. Thus, neural network parameters are fine tuned for each profile to generate the best results.

*D. Demand side management (DSM)*

DSM most commonly serves the purposes of peak clipping, valley filling, load shifting, load growth, load conservation or to make the load shape flexible [1]. As discussed in the introduction, load shifting is the most commonly used DSM technique, particularly with development of smart loads, the deferrable loads can automatically respond to the utility signals. Therefore, this study incorporated load shifting with different levels of demand flexibility ranging from 10% to 90%. This helps in quantifying the impact of consumer participation on the objective function. A comparison has been made between cost saving by DSM application for raw forecasted profile and alternate forecasted profile both with and without PV.

An important aspect in DSM application at distribution system level using the smart meter data is selection of the appropriate consumers. The appositeness of the consumers is decided by the cluster load profiles and it should be such that causes minimum disruption to the consumers and avoids customer fatigue.

Thus, the objective of cluster selection should enable DSM to achieve maximum cost savings with minimum consumer disruption. To achieve this, an algorithm (Fig. 2) is developed which selects the clusters based on an index considering per consumer energy density in each cluster during the peak load hours in combination with the forecast error. The clusters with the highest index are selected first for DSM. Before selection of the clusters, total system load is quantified using the summation of all cluster loads. The peak hours are identified from the system load curve. In this study, the periods with load beyond 85% of the maximum system load are considered peak hours. The peak is result of combined load by all clusters as given in (1);

$$EP_T = \sum_{i=1}^{k} EPC_i \qquad (1)$$

Where, $EP_T$ represents the total energy consumed by the system during peak hours and $EPC_i$ represents the energy consumed by cluster '$i$' during peak hours. Average energy consumed by each member of cluster '$k$' quantified as in (2);

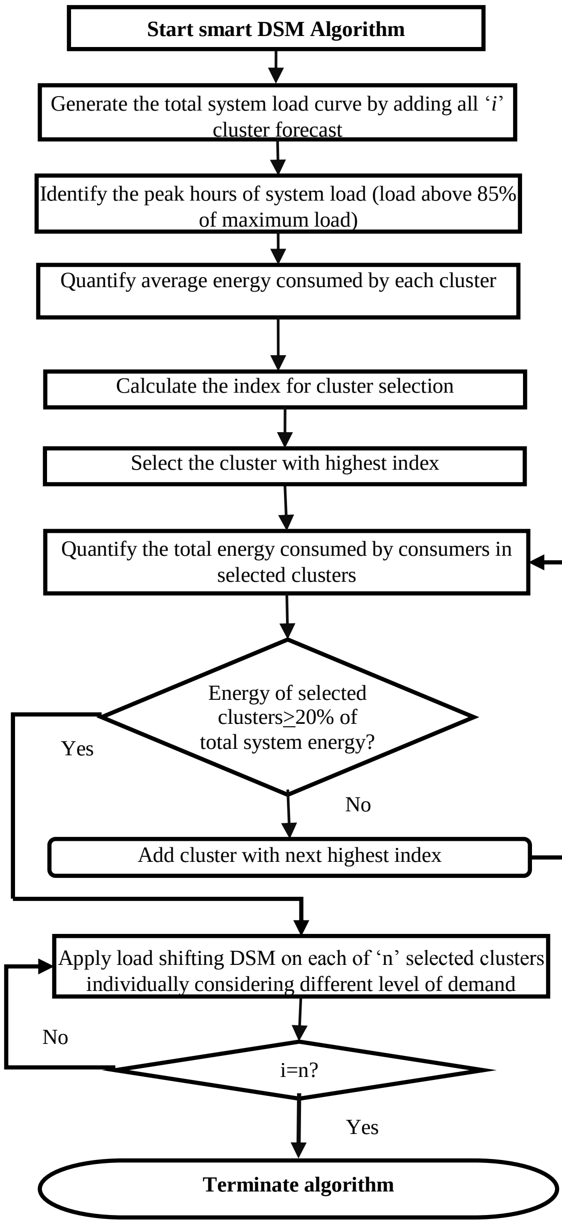



Fig. 2. Smart DSM algorithm

$$EC_k = EPC_k / N_k \qquad (2)$$

$EC_k$ represents the average energy consumed by members of cluster '$k$' during peak hours. $N_k$ is number of consumer in cluster '$k$'. Finally, the selection index '$S$' is calculated using (3).

$$S = EC_k + EC_k * (MAPE/100) \qquad (3)$$

The cluster selection index '$S$' incorporates the impact of the mean absolute percentage error (MAPE) by adding the energy difference due to the MAPE. The MAPE is taken from the available historic forecast error of each cluster. The index $S$ helps in selection of clusters with low number of consumers and in turn provides the utility an opportunity to identify the target group of consumers for DSM participation.

Clusters are selected using the selection index starting with the single cluster which carries the highest value of '$S$'. The selected cluster is evaluated for the percentage of the system energy. If the energy of the cluster is less than 20% of the system energy, cluster with next high value of the index is added to selection. At each point, the selection is checked to be a minimum of 20% of the system load so that when applying the demand flexibility, a minimum of two percent impact on the system load can be achieved i.e. with 10% demand flexibility. Once the selection is finalized, the selected clusters are utilized for DSM.

The objective of DSM application in this study is to acquire maximum saving for the consumer by minimizing the energy consumption during peak hours when the electricity prices are higher as compared to off-peak hours. The DSM optimization problem is solved using linear programming. The optimization problem can be mathematically formulated as in (4);

$$\text{minimize} \sum_{i=1}^{k} (C_i) \tag{4}$$

Where, $C_i$ is the cost of energy consumed at time $i$ and is defined in (5);

$$C_i = L_i * P_i \tag{5}$$

$L_i$ is forecasted load at time $i$ given in kWh and $P_i$ gives the price of energy at the time $i$ and is given in pence/kWh. To ensure that the energy before and after optimization remains the same, an equality constraint is introduced (6);

$$\sum_{i=1}^{k} ER_i = \sum_{i=1}^{k} ED_i \tag{6}$$

Where $ER_i$ represents the real energy consumed and $ED_i$ gives energy after the demand side energy management. Two Scenarios are considered for the upper bound of the optimization variable. In the first Scenario, the upper bound is set to equal peak value of the cluster, whereas in the second case peak shaving of 5% is considered.

Impact of solar PV integration at cluster level has also been analysed by incorporating 10% PV penetration in each cluster. However, this is considered as a data pre-processing element by using simulated PV profiles to reduce the system load as per PV generation during the day.

## III. Numerical Application and Results

For the case study, smart meter data for more than 5000 homes and businesses from Ireland [16] with 30 minutes data resolution is used for clustering. The clusters are used to extract the alternate profiles which are used to forecast load for the next one week (168 hours) in half hour intervals. Fig. 3 shows raw and alternate profiles of a cluster to demonstrate the difference between the two profiles.

The linearization process is applied to both PV and load

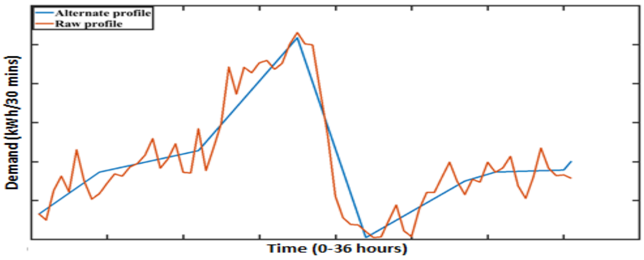


Fig. 3. Raw and Alternate Profile

profiles to create alternate load and generation profiles. For incorporation of the PV profile into the load profile, the simulated PV profile is normalized between 0 and 1 and multiplied with 10% of the average cluster load before subtracting it from the cluster load. These profiles are used for short term load forecast.

A comparison of forecast accuracy for raw and alternate profiles with and without PV integration is carried out. It can be clearly seen from Fig. 4 that the alternate profiles demonstrate better forecasting accuracy than the raw profiles. The MAPE with and without PV does not vary significantly in majority of the clusters because the overall reduction due to PV in the entire distribution system load is nearly 2% of the total distribution system energy during the day. An increase in the PV capacity can potentially have a higher impact on the forecast accuracy.

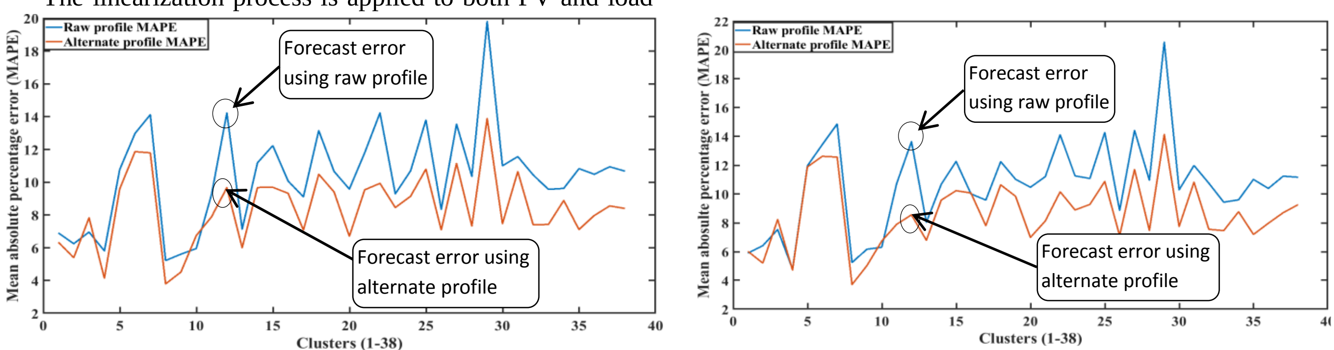
Two DSM cases are simulated with each case considering two DSM Scenarios for raw and alternate profiles. The price of electricity to determine the cost of total energy consumed is considered dynamic with Time-of-Use Tariff i.e. higher rates for peak hours and lowers for off peak hours. The clusters selected for DSM application are 10 clusters having 5% consumers and 28% load and 15 clusters having 10% population and 32% load. High number of cluster selection was used to produce distinct solutions to differentiate between the two approaches i.e. DSM using raw profiles and alternate profiles. The cases are briefly discussed below.

### A. *CASE I*

In the first case, the smart meter data is considered for load forecasting and then DSM application. PV generation is not considered. Two different Scenarios are simulated for case I and both Scenario compare the results of DSM application using raw and alternate profiles. The Scenarios and results are given in the following;

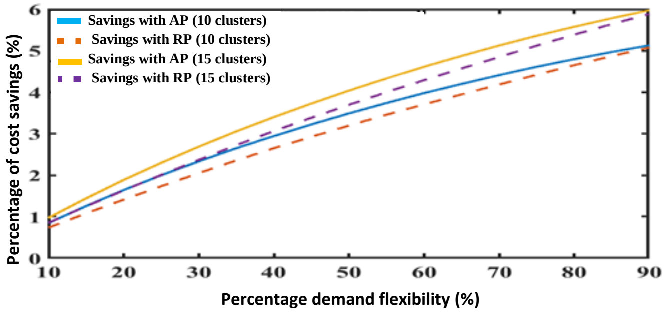
1. Scenario I

In the first Scenario, the objective function is set to minimize the cost of energy consumption to maximize the

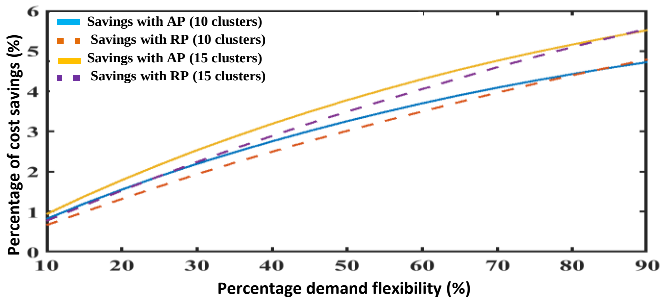


(a) MAPE for different clusters without PV integration (b) MAPE for different clusters with 10% PV generation

Fig. 4. Forecast error for clusters with and without PV for raw and alternate profiles (X-axis show cluster and Y-axis show MAPE)




(a) Scenario I




(b) Scenario II

Fig. 5. Case I (Without PV): Cost saving and peak reduction by load shifting (Alternate profile (AP),Raw profile (RP))

savings of electricity consumers. The constraints include an equality constraint to ensure that the total energy consumption over the day should remain constant. The upper limit of the objective profile is set as the maximum value of load in the cluster profile. This limits the maximum value of load and limits the load to the existing peak.

Scenario I is simulated using the raw and alternate forecasted profiles to compare their efficacy. Fig. 5a shows cost saving for raw and alternate profiles in Scenario I. It is clear from the Fig. 5a that except 90% demand flexibility, the alternate profiles propose higher cost saving. Impact of level of selected clusters load on the DSM for raw and alternate profiles is proportional and overall dominance of alternate profiles stays unchanged.

Despite optimum cost saving for consumers, the utility can face another peak which can be higher than previous peaks, however this can be handled by coordination between the different clusters or by choosing the right level of demand flexibility as secondary load control.

2. Scenario II

Scenario II considers load shifting with peak shaving of 5%. As the upper bound is reduced to 95%, the freedom for the optimization variable to find global optima reduces thus overall cost savings using peak shaving reduces as compared to Scenario I. The alternate profiles once again provide higher cost saving solution as compared to the raw profiles. Fig. 5b shows the cost saving for raw and alternate profile for Scenario II.

### *B. CASE II*

Case II simulates the DSM application on the load profiles which have already incorporated PV generation of 10%. Raw profiles incorporated raw PV profiles while the alternate profiles were incorporated with alternate PV profiles (linearized generation profiles). Two Scenarios (as in Case I) are considered to simulate DSM for PV integrated loads. The same clusters are selected by the cluster selection algorithm as in Case 1.The selected clusters are used for DSM application and two Scenarios considered for DSM are described below;

1. Scenario I

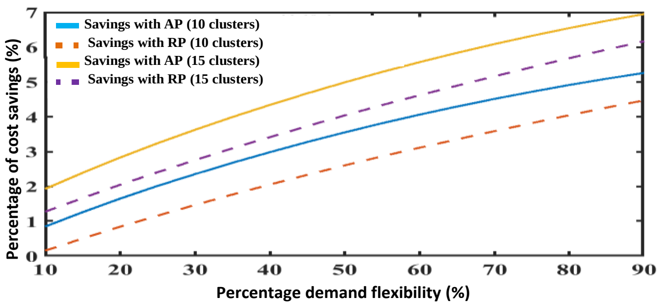
Scenario I in case II considers similar conditions as in Scenario I of case I. As described above, all clusters are already incorporated with PV generation. The results given in Fig. 6a show that there is a significant improvement in the cost saving for alternate profiles and only slight improvement in savings with raw profiles. The intermittency of the PV increases the non-linearity of the raw profile and consequently the solution provided by linear programming is not optimum as compared to the alternate profiles where the profiles were more convex resulting in a better solution.

2. Scenario II

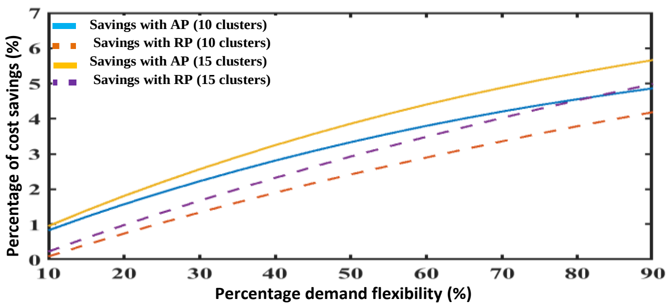
Scenario II considers the raw and alternate profiles with 10% PV penetration for load shifting with 5% peak shaving. From Fig. 6b it is evident that for Scenario II, the cost savings face a slight reduction as compared to case I. However, interestingly in this Scenario, even 10 clusters of raw profiles showed higher savings as compared to the 15 raw clusters DSM. This relates to non-linearity of the higher level of load for raw profiles as the intermittent PV profiles were non-linear and they added to the non-linearity of the existing profile. Whereas, the alternate generation (PV) profiles were incorporated in alternate profiles thus the convexity of the alternate profiles was maintained.

A comparative analysis of both cases suggests that alternate profiling method produces better DSM optimization solutions with higher cost savings as compared to raw profiling method. The savings increase with increase in the load for DSM as the flexibility to find the optimum solution increases.

An overview of the results for both cases shows that higher demand flexibility results in higher cost savings. Although the second Scenario of peak shaving tries to control occurrence of second peak, the combination of different cluster loads can potentially create another peak.

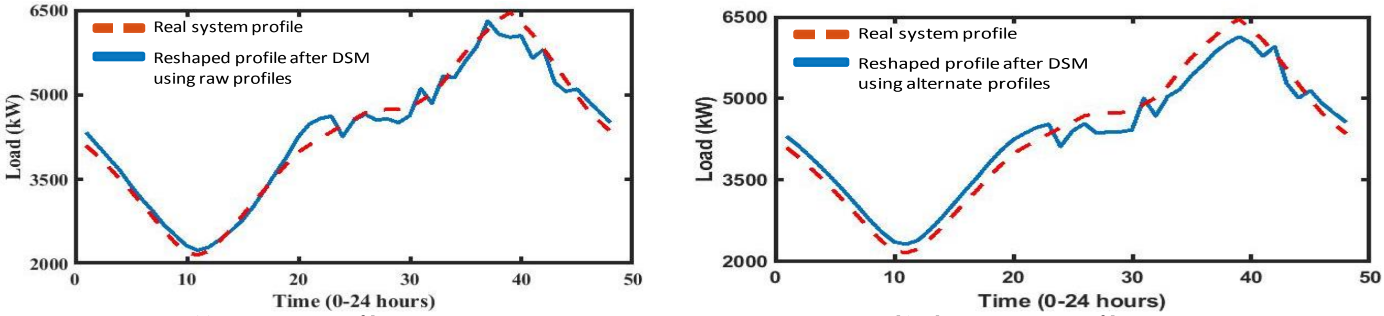



(a) Scenario I




(b) Scenario II

Fig. 6. Case II (with PV): Cost saving and peak reduction by load shifting (Alternate profile (AP),Raw profile (RP))




(a) Raw system profile DSM

(b) Alternate system profile DSM

Fig. 7. System profiles before and after DSM application (15% demand flexibility)

This can be controlled by using different levels of demand flexibility of the clusters. It has been observed that the peak of load starts to rise after 25% demand flexibility. Therefore, the threshold of demand flexibility should be 25% to ensure a smoother system profile with reduced risk of rebound. The results also show that the alternate profiles provide relatively better DSM solution at lower demand flexibility as compared to the traditional DSM approach which uses raw profiles. This is primarily due to the inherent non-linearity of the raw cluster profiles leading to sub optimal solutions. The non-linearity leads to highly non-convex behaviour of the raw profiles and linear optimization techniques do not necessarily provide the optimal solutions for such profiles.

It is important to see the impact of DSM optimization at individual cluster level to the reshaped system profile. The reshaped profile in Fig. 7 (scenario I, Case II) signifies the benefit of linearity of alternate profiles. The system profiles shown in the Fig. 7 demonstrate relatively smoother and uniform reshaped system profile for alternate profile as compared to the raw profile. Due to the limitation of demand flexibility, the overall growth or reduction in the cluster load for the cases of raw profiles tends to be non-linear and consequently non-linear reshaped profiles. The alternate profiles produce linear boundaries for optimization problem with linear constraints resulting in optimal solution. The solution provided using raw cluster profiles does not provide a uniform load growth and reduction of load which is eminent in the alternate profiles.

With the evolution of new technologies, modelling energy consumption at every node is highly intricate and challenging process. This is particularly eminent in applications where the non-linear functions are required to be processed using linear techniques. The paper has presented a smart approach for DSM where load profiles of smart meter consumers are clustered and the N-dimensional non-linear data functions are systematically linearized to concatenation of linear profiles which are used for DSM optimization. The convexity of data functions has been tested for DSM optimization and results have validated the applicability and effectiveness of the approach with case studies.

## IV. Conclusion

Demand side management has the potential to provide benefits at the power distribution level. An innovative approach for DSM application at the power distribution system level is proposed in this paper by incorporating smart meter data. The approach used extended k-mean clustering and linear programming for DSM application by incorporating alternate profiles to enhance the convexity of non-linear profiles.

The results using the proposed approach show significant increase in monetary benefits at lower demand flexibility levels as compared to the conventional approach. The paper also argues that proposed DSM approach provides true benefits for the electricity consumers for their participation in the DSM process.

## Acknowledgment

This work is supported by the University of Birmingham, United Kingdom (U.K.) and Mirpur University of Science and Technology (MUST), Mirpur (AJK) Pakistan.

## References

[1] P. Palensky and D. Dietrich, "Demand Side Management: Demand Response, Intelligent Energy Systems, and Smart Loads," *IEEE Transactions on Industrial Informatics*, vol. 7, pp. 381-388, 2011.

[2] D. S. Kirschen, "Demand-side view of electricity markets," *IEEE Transactions on Power Systems*, vol. 18, pp. 520-527, 2003.

[3] T. Logenthiran, D. Srinivasan, and T. Z. Shun, "Demand side management in smart grid using heuristic optimization," *IEEE transactions on smart grid*, vol. 3, pp. 1244-1252, 2012.

[4] G. Strbac, "Demand side management: Benefits and challenges," *Energy Policy*, vol. 36, pp. 4419-4426, 2008/12/01/ 2008.

[5] C. W. Gellings and J. H. Chamberlin, "Demand-side management: concepts and methods," 1987.

[6] B. Pitt and D. Kitschen, "Application of data mining techniques to load profiling," in *Power Industry Computer Applications, 1999. PICA'99. Proceedings of the 21st 1999 IEEE International Conference*, 1999, pp. 131-136.

[7] J. MacQueen, "Some methods for classification and analysis of multivariate observations," in *Proceedings of the fifth Berkeley symposium on mathematical statistics and probability*, 1967, pp. 281-297.

[8] J. C. Dunn, "A fuzzy relative of the ISODATA process and its use in detecting compact well-separated clusters," 1973.

[9] D. Pelleg and A. W. Moore, "X-means: Extending k-means with efficient estimation of the number of clusters," in *Icml*, 2000, pp. 727-734.

[10] Z. A. Khan and D. Jayaweera, "Planning and Operational Challenges in a Smart Grid," in *Smart Power Systems and Renewable Energy System Integration*, ed: Springer, 2016, pp. 153-177.

[11] A. Ghasemi, H. Shayeghi, M. Moradzadeh, and M. Nooshyar, "A novel hybrid algorithm for electricity price and load forecasting in smart grids with demand-side management," *Applied Energy*, vol. 177, pp. 40-59, 2016/09/01/ 2016.

[12] Z. A. Khan, D. Jayaweera, and M. S. Alvarez-Alvarado, "A novel approach for load profiling in smart power grids using smart meter data," *Electric Power Systems Research*, vol. 165, pp. 191-198, 2018.

[13] X. Rui and D. Wunsch, "Survey of clustering algorithms," *IEEE Transactions on Neural Networks*, vol. 16, pp. 645-678, 2005.

[14] Z. A. Khan and D. Jayaweera, "Approach for forecasting smart customer demand with significant energy demand variability," in *2018 1st International Conference on Power, Energy and Smart Grid (ICPESG)*, 2018, pp. 1-5.

[15] K. L. Ho, Y. Hsu, and C. Yang, "Short term load forecasting using a multilayer neural network with an adaptive learning algorithm," *IEEE Transactions on Power Systems*, vol. 7, pp. 141-149, 1992.

[16] Available: ISSDA, CER Smart Meter Customer Behaviour Trials Data, accessed via the Irish Social Science Data Archive, CER Electricity, Accessed via www.ucd.ie/issda (revised March2012)