2019

Demand Response and Consumer Inconvenience

Chittesh Veni Chandran

Malabika Basu

Keith Sunderland

Demand Response and Consumer Inconvenience

Chittesh Veni Chandran
Technological University Dublin
School of Electrical and Electronic Engineering
Dublin, Ireland
chittesh.vc@mydit.ie

Malabika Basu
Technological University Dublin
School of Electrical and Electronic Engineering
Dublin, Ireland
malabika.basu@dit.ie

Keith Sunderland
Technological University Dublin
School of Electrical and Electronic Engineering
Dublin, Ireland
keith.sunderland@dit.ie

***Abstract*— Balancing the energy demand and generation using the latest load management technologies is considered as an immediate requirement for peak demand management and to improve the operation of electrical distribution networks. However, load management technologies depriving consumers of utilizing their personal resources could be perceived as a consumer right violation by many consumers, and thus, the success of the program is significantly dependent on consumer satisfaction. This paper probes consumer engagement plans through an algorithm to minimize the consumer inconvenience caused by the load management/ demand response (DR) program. Four different consumer engagement plans are proposed for consumers with different tolerance levels, starting from most tolerant to the least. Based on the engagement plans chosen, the reduction requests are generated by the algorithm. The second stage of the algorithm will schedule devices to meet the consumer demand and demand reduction request. The mixed integer linear programming (MILP-DR) algorithm, is implemented on a distribution network model. The uniqueness of the algorithm is the consumer tolerance (comfort) levels are given due consideration, based on a fairness of participation basis in the scheme. The is weight updating factor updates the tolerance of the consumer based on their participation (load reduction and duration of reduction).**

Keywords*— *Consumer Comfort, Demand response, demand side management, Integer linear programming, Load management

NOMENCLATURE

m	*Number of devices,* $\boldsymbol{i} \in \{\mathbf{1, 2, 3, \ldots \ldots m}\}$
n	*Number of consumers,* $\boldsymbol{j} \in \{\mathbf{1, 2, 3, \ldots \ldots n}\}$
A	*Array of consumer device demand*
D	*Device status in household* $\in \{\mathbf{0, 1}\}$
B	*Array of allowed devices*
R	*Array of denied devices*
P	*Active Power*
$\propto$	*Consumer tolerance*
$\boldsymbol{\beta}$	*Device inconvenience*
$\boldsymbol{\Delta P}$	*Load reduction*
$\boldsymbol{P_{Peak}}$	*Peak demand*
$\boldsymbol{P_{Total}}$	*Total load*

I. INTRODUCTION

A. Motivation and Background

In recent years, the electrical power distribution sector has been focused on the prospects of optimizing their distribution to micromanage the load curve, which would enable them to reap benefits from the energy markets. The remarkable development of information and communication technologies has enabled the opportunity for managing demand side resources to benefit its participants. The technique of micromanaging the load curve by manipulating the demand side resources with active participation from consumers is termed as demand response (DR). Demand response is a series of activities that respond to the peak demand or electricity price by regulating or restricting the operation of consumer equipment resulting in benefit for all parties involved. However, such a DR program has to contend with different passive quantities in the system increasing the complexity of such programs. Along with the different ranges of devices involved, the challenges faced by DR programs are an ongoing concern [1]. One such challenge, consumer comfort violation, has been a major bottleneck for the success of any DR programs [2]. This is because the deviation of the end users normal consumption will lead to consumer discomfort or inconvenience. Generally, incentives for bearing this inconvenience are not attractive and hence, the load management programs are not appreciated in the consumer market. This, when considered as an EU opportunity to reduce peak demand by 60GW (approximately 10%), introduces a moral dilemma to investors and network operators whether they should invest in these kinds of load management techniques.

B. Relevant Literature

Naeem *et.al* [1] investigate the dependencies of DR programs on social and economic factors. In [3], Hassan *et. al*, indicate a relationship with consumer inconvenience and DR and how the inconvenience to consumers increases with the magnitude of load increases. This influences the participation of consumers in a DR program as consumer inconvenience can be considered as the direct measure of consumer comfort. Further, the importance of consumer awareness and clarity of information to consumers are discussed in [4]. The same paper proposes a consumer engagement DR plan to control a central heating thermostat. Also, the European Commission [5], contends that consumers should be given the right incentives to encourage more active engagement and contribution to system performance and stability.

In literature, various DR models are proposed [6][7][8], with DR programs mainly classified into two categories: *Price-based* methods and *Incentive-based* methods. However, based on the cost incurred, technology utilised, the implementation level, etc., DR can again be classified into various categories [9]. Furthermore, DR has been proposed as a solution for not only the peak management problem, but also as a solution for maximizing PV consumption, optimizing battery storage, exploiting the electric vehicle flexibility, manage reliability issues, manage emission and much more [9] [10] [11]. In spite of these added benefits, the main objective of a DR program has always been load curve smoothing. The recent trend technologies used for implementing DR in the literature suggest an increased interest in applying machine learning to DR [12][13]. Other general techniques include, model predictive control [14], heuristic optimization based [15], agent-based modelling [16], mixed integer programming [17] etc. However, the choice of tool usually depends on the objective/application of DR and is chosen by the programmer based on the specific requirements and intuition. In the presented work a mixed integer linear programming (MILP) based technique is utilized based on the

978-1-7281-1156-8/19/$31.00 ©2019 IEEE

literature reports on similar problems and its ease of modelling.

C. Contributions

This paper investigates the idea of introducing a consumer tolerance based consumer engagement plan to minimize the consumer inconvenience associated with a DR program. The MILP-DR algorithm responds to the change in consumer tolerance while maintaining *fairness* between different consumers. The algorithm is able to reschedule the load rather than only curtailing it, which further enhances consumer acceptances of DR programs. The following section discusses the engagement plans and MILP-DR modelling.

II. METHODOLOGY

The DR program presented here is executed at two levels: aggregator level and consumer level. At aggregator level, the DR program is initiated with the load reduction request from the utility, which is subsequently divided among the participating consumers based on their (current) tolerance value. This forms individual house demand reduction requests. The second stage of the program is executed at the consumer level which schedules the different domestic appliances. The schedule is based on the individual device/appliance inconvenience values dictated by the consumer. The objective is to minimize the overall inconvenience in order to achieve the required load reduction.

In order to distribute the demand reduction request in the first stage, a consumer engagement plan is initiated and presented based on tolerance.

A. Consumer engagement plans

The proposed techniques require the consumer to be facilitated with consumer engagement plans at different levels so as to recruit the consumer to take part in the energy management opportunities provided by DR. The engagement plan can be devised considering various factors, however, to simplify the concept here, only one major factor is considered: consumer inconvenience. When considered as a factor, consumer inconvenience can directly co-relate with the incentive offering and can be thus utilized to formulate the incentive program as well (not considered in the scope of this paper). Yet again, the engagement of a domestic consumer in the load reduction plans are not very well motivated by the monetary benefits offered by it, rather, from literature, it has been observed that a persistent motivation for the DR schema can be reaped by correlating the benefits to non-tangible gains such as environmental factors. From these understandings, four type of consumers are identified:

Super Green Savvy: users that tolerate a higher amount of inconvenience as they are aware of the social benefits of DR program and are also highly motivated. .

Green Savvy: users are motivated to join the program due to its benefits but are only moderately tolerant of load change.

Green Aware: users who are willing to participate with the DR program but, do not tolerate high inconvenience and obviously are afforded a lower incentive.

Reluctant: users who are sceptical and are not willing to participate in the program and thus will not contribute to the load reduction desired by the grid operator.

For each type of consumers, a tolerance factor is defined given by ($\alpha \epsilon (0,1)$). The value of α can be anywhere from 0 to 1 being a fraction. The tolerance factor has an inverse relation with the consumer inconvenience and direct relation to the amount of load reduction possible. The value of tolerance will increase/decrease with the selection of a consumer in an interval depending on the activity in the previous intervals. This ensures that consumers having high tolerance will not be chosen repeatedly to manage load reduction. This tolerance change associated with the consumer, will be calculated in two parts. The first part depends on the time period for which the operation of a device is restricted. The second part accounts for the kilowatt reduction imposed. The first part is the major component in updating the weight (α), but, the second part would have higher influence if incentives are calculated.

B. Mixed integer programming for DR

The objective of a DR program is to produce a control signal to restrict the use of electrical loads to obtain the required reduction/increase in the total electric demand. This objective is constrained by a set of operation and security conditions and hence is to be modelled in an elaborate manner. The implementation will be executed in CVX using a MOSEK solver in a MATLAB environment.

Now, let there be 'n' number of consumers. So the total power consumed at a given time't' is given by

$$P_{Total}(t) = \sum_{j=1}^{n} P_j(t) \qquad (1)$$

Where, $P_j(t)$ is the power consumed by the consumer. The time dependency factor is dropped from here on as it will not impact the analysis once the time interval is defined. Further, each consumer may have 'm' number of devices in their dwelling. Now the total power consumed is given by at a given time 't' is given by

$$P_{Total} = \sum_{j=1}^{n}\sum_{i=1}^{m} P_{ij} \qquad (2)$$

Where, $i \in \{1,2,3,\dots\dots m\}$, $j \in \{1,2,3,\dots\dots n\}$ and P_{ij} is the power consumed by the i_{th} device of the j_{th} consumer. The domestic loads are categorized broadly as dispatchable and non dispatchable loads. Dispatchable loads are those that can be denied operation and are also known as non-critical loads. Non-dispatchable loads, however, are those that cannot be regulated or denied operation when demanded by the consumer and are also known as critical/emergency loads. The total power demand of the house at a given time is contributed by the non-dispatchable and dispatchable devices. So the total power consumed can be re-written as,

$$P_{Total} = \sum_{j=1}^{n}\left(\sum_{i=1}^{m}\left({P_{ij}}^{ND} + {P_{ij}}^{D}\right)\right) \qquad (3)$$

${P_{ij}}^{ND}$ is an array of power consumed by the individual non-dispatchable devices and ${P_{ij}}^{D}$ represents the array of power consumed by the individual dispatchable devices.

At an instance, the total demand status can be given by a demand status array which represents the status of the devices.

$$\mathrm{A} = \begin{Bmatrix} \mathrm{A}_1 \\ \mathrm{A}_2 \\ \mathrm{A}_3 \\ \vdots \\ \mathrm{A}_n \end{Bmatrix} \qquad (4)$$

$$A_j = \{D_1 \quad D_2 \quad D_3 \quad \dots \quad \dots \quad D_m\} \tag{5}$$

Where, $D \in \{0, 1\}$, which is the status of the devices 'D' at the house and indicate 'ON' if it is '1' and 'OFF' if it is '0'. The array A gives the status of all devices in the house and hence the critical devices will have a status 1 when demanded and would not be changed by the DR management algorithm. In effect, A_{ij} gives the status of the i_{th} device of the j_{th} consumer. Now, the total power consumed equation can be re-written as

$$P_{Total} = \sum_{j=1}^{n}\left(\sum_{i=1}^{m} A_{ij}\left(P_{ij}{}^{ND} + P_{ij}{}^{D}\right)\right) \tag{6}$$

The demand status array, A_{ij} is time dependent and changes with time, thus providing the operator the requirement of a consumer at any given time. To perform DR or energy management, the grid operator issues a load reduction request or may define a peak load (P_{Peak}). In either case, the DR management scheme is supposed to perform load reduction, which is given by

$$\Delta P = P_{Total} - P_{Peak} \tag{7}$$

The first stage of the DR scheme is to distribute this load reduction to different consumers throughout the grid based on the consumer tolerance factor $\propto_j$ or engagement plan. Consequently, the objective is to

$$minimize\left(\sum_{j=1}^{n}\left(\propto_j \Delta P_j\right)\right) \tag{8}$$

Where, ΔP_j is the individual power reduction demanded from the consumers. The reduction should not be excessively burdensome for a consumer, hence, a maximum possible reduction constraint of 50% is imposed to individual consumers. Other constraints the objective is subject to are,

$$\Delta P = P_{Total} - P_{Peak} \tag{9}$$

$$\Delta P_j \leq 0.5\, P_j \tag{10}$$

$$\Delta P \leq \sum_{j=1}^{n} \Delta P_j \tag{11}$$

$$0 \leq \propto_{ij} \leq 1 \tag{12}$$

This forms the first stage of optimization where the load reduction required is distributed to the consumers based on their tolerance limit. However, while this objective is achieved in subsequent time intervals the algorithm needs to account for the fairness in how consumers for DR management are selected, and hence requires a consideration of the following factor,

- The same consumer should not be given the burden of reducing demand in every time.
- There should be fairness between consumers choosing same engagement plans for overall participation.

Initially, the tolerance associated with each consumer is by default set to the same value for a consumer choosing a particular consumer engagement plan. However, in any interval, if a particular consumer is chosen for load reduction, the tolerance value increases for the next iteration. This ensures that the same consumer, having the lowest tolerance value, will not be given the burden to reduce the demand in the subsequent intervals or the amount of reduction requested will at least be reduced. This increase in the weighting of tolerance will be influenced by two factors. One, the time for which the consumer is imposed restriction, and two, the amount of power reduction imposed. Further, the maximum reduction per consumer is also restricted to 50% of total demand to ensure that a particular consumer will not be penalized for having lower value of tolerance factor (α). Once this stage is completed, the second stage of optimization with the objective of deciding the devices that need to alter its state of operation is to be identified. This total reduction contribution from each house was proposed by the previous stage. The output of the second stage is to produce a device operation status array B, which provides the information of a list of devices operating after DR engagement.

$$\mathrm{B} = \begin{Bmatrix} B_1 \\ B_2 \\ B_3 \\ \vdots \\ B_n \end{Bmatrix} \tag{13}$$

$$B_j = \{D_1 \quad D_2 \quad D_3 \quad \dots \quad \dots \quad D_m\} \tag{14}$$

Where again, $D \in \{0, 1\}$, which is the status of the devices 'D' at the house and indicate 'ON' if it is '1' and 'OFF' if it is '0'. In effect, gives the status of i_{th} device of j_{th} consumer. The devices denied operation can be given by

$$R_{ij} = \left(A_{ij} - B_{ij}\right) \quad \forall\ i\ \in m, j\ \in n \tag{15}$$

The amount of load reduction achieved can be given by,

$$\Delta \mathrm{P} = \sum_{j=1}^{n}\left(\sum_{i=1}^{m} R_{ij} P_{ij}{}^{D}\right) \tag{16}$$

Corresponding to the consumer tolerance, there is an inconvenience associated with each device. The inconvenience is different if a consumer is being denied the use of washing machine to being denied the use of television. Thus, different devices will have a different inconvenience factor and given by, β_{ij}, which is the inconvenience associated with altering the operation of i_{th} device of j_{th} consumer. This value forms a priority list of devices in a domestic environment. Further, the consumer will always have an option to set different priorities for the devices in their household. The objective function is to

$$Minimize\left(\sum_{\mathrm{i}=1}^{m} \beta_i R_i\right) \tag{15}$$

Subject to constraints,

$$\Delta \mathrm{P} \leq \sum_{i,j=1}^{n,m} R_{ij} P_{ij} \tag{16}$$

$$0 \leq \beta_{ij} \leq 1 \tag{17}$$

$$\Delta P \leq \sum_{j=1}^{m} \Delta P_j \tag{18}$$

The sum of load reduction by individual houses will be equal to or less than the total reduction required by the operator. Cases may occur where total reduction is not achieved due to a limitation imposed by constraints. Under these circumstances the algorithm is set to scale down the reduction request by 20% and proceed to solve. The process continues until an optimal solution is obtained.

III. Results and Discussion

To perform an alteration in consumer demand, an estimate of consumer demand is required ahead of time. In this research, a domestic device power consumption dataset for a single house is utilized as a demand array. The dataset contains individual power consumption of different devices (12 devices) in the domestic environment with a resolution of 1sec. An average load consumption data model was derived from the measured data to provide the demand for every 15 minutes. For each house, the same data set is used to constitute 74 domestic houses, which serves the same load profile for each individual consumer for the day. This provides an accurate view of the performance of the algorithm towards the consumer inconvenience as the only varying factor.

To begin with, the DR program is expecting a reduction request from the operator at a given time. Random reduction requests were generated for load reduction. The stage one (aggregator level) of the program, dictates the individual reduction demanded from each consumer based on the tolerance value. The tolerance level of the consumers are initiated as per their engagement plans and later updated using the weight update algorithm. The distribution of consumers into the four engagement plans and their corresponding tolerance level is provided in TABLE I. The section also calculates the total demand in the network and checks the feasibility of the demand reduction request. In the presented case, if the overall demand reduction request is more than 40% the algorithm fails to find an optimal solution and thus will return an infeasibility error. This occurs due to the maximum limit bounding of the algorithm which ensures a feasible solution without overburdening the consumers. This limit is influenced by the total load, the number of consumers, demand of each consumer, the engagement plan, and the amount of dispatchable load. Hence, this limit is variable depending on the scenario

TABLE I. Distribution of Consumers Based on Engagement Plans

Consumer Engagement Plans	Tolerance (α)	Percentage of Consumers
Super Green Savvy	[0.2 – 0.5)	30%
Green Savvy	[0.5 – 0.7)	27%
Green aware	[0.7 – 1)	35%
Reluctant	1	8%

The input to the second part of DR optimization is the load reduction request for individual consumers based on which device operation schedule is generated. This optimizes the device operation in the house based on the inconvenience value defined for each device. The inconvenience value can be defined by consumers. However, in the presented research, this value is assumed based on a general idea about the device as well as allowing enough breathing space for the algorithm. Certain devices are categorized as non-dispatchable devices and hence would not be altered during the optimization. The list of devices considered in a domestic environment are given in TABLE II along with their corresponding inconvenience factor and category. The list is in accordance with the domestic load data set used in the first part of the algorithm. In the presented scenario, the assumed inconvenience value is considered common for all 74 consumers. The inconvenience factor can always be input and altered by the user. A consumer who has a larger load to control with lower inconvenience factor may automatically qualify to be in the highest tolerance plan. From TABLE II, the inconvenience factor is 1 (the highest inconvenience) for non-dispatchable devices and different values (0, 1] for dispatchable devices. The inconvenience value directly represents the inconvenience faced by the consumer if the device is not allowed to operate during its demand.

TABLE II. Device List and their Inconvenience

	Device	Inconvenience (β)	Category
1	Cooker	1	Non Dispatchable
2	Toaster	1	
3	Television	1	
4	Socket (Wi-fi)	1	
5	Microwave	1	
6	Laptop Computer	0.45	Dispatchable
7	Electric Heating Element	0.1	
8	Oven	0.45	
9	Fan	0.2	
10	Fridge	0.4	
11	Socket (Mobile)	0.35	
12	Washing Machine	0.2	

The simulation is performed for every 15 minutes forming 96 intervals representing a 24-hour period (one day). The demand for each period is updated using the previous allowed load and the new requirement. The tolerance of each consumer is updated in each interval based on their participation.

The major focus is set forth for the algorithm to capably manage consumer load reduction between consumers while causing minimal impact to consumer comfort. Hence, if the demanded load reduction is not achievable the algorithm steps the demand reduction down to a lower value and keeps on doing so until a feasible solution is obtained. Further, if a device is denied operation, it is recorded and subsequently requested to operate by the algorithm during the off-peak time which forms the time shifting of device operation. This ensures the consumer requirements are met during the day. However, certain devices such as the heater and fridge are not brought back for total intervals for which it was denied operation as they are able to retain its stable operation for 2-3 intervals without compromising its performance. This in effect reduces the load consumption while improving energy efficiency. The DR is performed only during the peak period which is isolated to be Morning (7:30AM to 10:30AM), mid-day (12:30PM to 02:30PM) and evening (7PM to 10:30PM). These timings have been selected based on intuition and can be altered whenever required, but they represent peak demand periods with respect to a general demand profile under consideration.

The aggregated load and DR load is presented in the TABLE III and is plotted in Fig 1. As stated before, all 74 consumers are assigned the same load demand which affords a better understanding of the sensitivity of the DR program to the consumer engagement plans. Figure 1 illustrates that during the off-peak intervals, the total load is increased when compared to the actual demand, depicting the load rebound which makes sure that all the necessary loads of the consumer are time-shifted and not deprived. From TABLE III, it can be observed that the total load reduction is less than the load reduction achieved by DR without considering consumer inconvenience. However, as observed in various pilot studies in the literature, the success of DR greatly depends on the consumer acceptance which has a direct correlation to the load rejection. The presented algorithm not only considers the load reduction at peak times but also accounts for consumer inconvenience. The necessary loads which are turned off during the peak are also returned which enhances the consumer conviction towards the program.

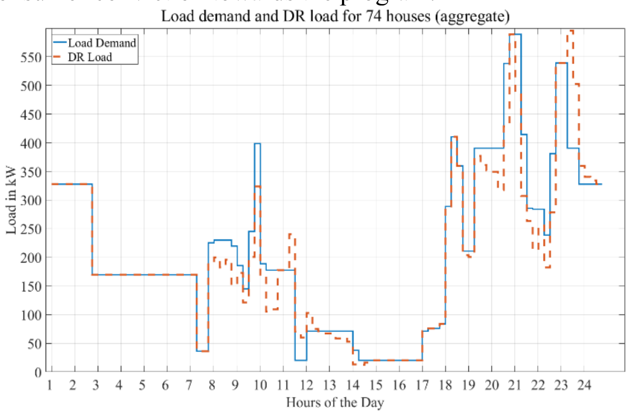

Fig 1. Total Load and DR load change for 74 consumer aggregate

Four representative consumers engaged in four different consumer engagement plans are chosen as an example. Figure 2 represents a Super Green Savvy consumer that is willing to endeavour in a high amount of load reduction if demanded, and hence starts with a very low value of tolerance. Essentially the lowest value α can have is 0. However, considering a practical point of view, this works assumes the lowest value possible to be 0.2. This was also supported by testing of the algorithm with various value and 0.2 provided a better convergence rate. The value of α for consumer in Fig 1. who chose the Super Green Savvy engagement plan increases for the next interval when they participate in the load reduction in the particular interval. When the consumer is not participating in the reduction the value of α decreases in fixed steps for each iteration until it reaches the default value set by the engagement plan. Compared to the consumer considered in Fig 2. , the consumer in Fig 3. who has chosen a Green Savvy engagement plan has a higher tolerance value and participates less in load reduction. Similarly, the consumer (in Fig 4. using the Green aware engagement plan participates less than Green Savvy consumer and facilitates a lesser load reduction. Figure 5 presents the amount of load management achieved for consumer participating in each engagement plan. The magnitude of reduction is based on the engagement plan which is proportional to the tolerance (consumer comfort). The load rebound after the peak period is also shown in the Fig 5. which ensure that most of the necessary loads of a consumer will be fulfilled during the off-peak period if deprived by DR during peak period.

Form these figures the capability of the algorithm to choose consumers based on their engagement plan can be observed. The MILP-DR can thus introduce fairness between consumers engaged with different engagement plans and also establish fairness to consumers by not choosing consumers with low value of tolerance repeatedly. The algorithm can be further modified in a similar way to include fairness between different consumer devices.

From TABLE III, it can be observed that the total reduction considered in this scenario was only 7%. However, during the operation, the algorithm was able to reduce up to 40% of total load (instantaneous) in certain intervals. As discussed earlier, this value depends greatly on a number of factors. Further, the table also compares the reduction achievable with MILP-DR with and without considering consumer inconvenience. The reduction achieved while considering consumer inconvenience is lower, yet the algorithm can attract more consumers and which would increase consumer participation leading to higher reduction possibilities.

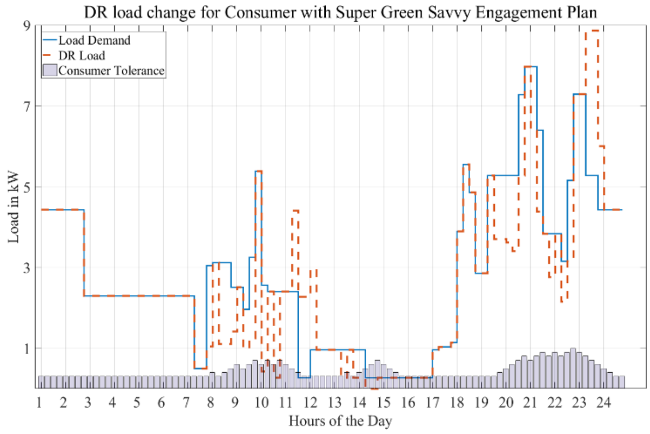

Fig 2. MILP-DR for Super Green savvy engagement plans

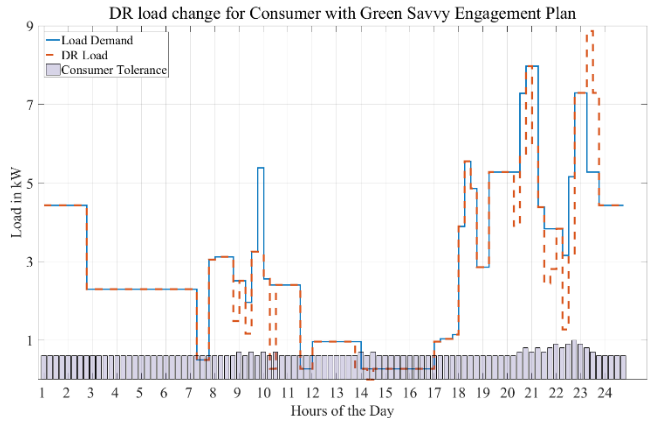

Fig 3. MILP-DR for Green savvy engagement plans

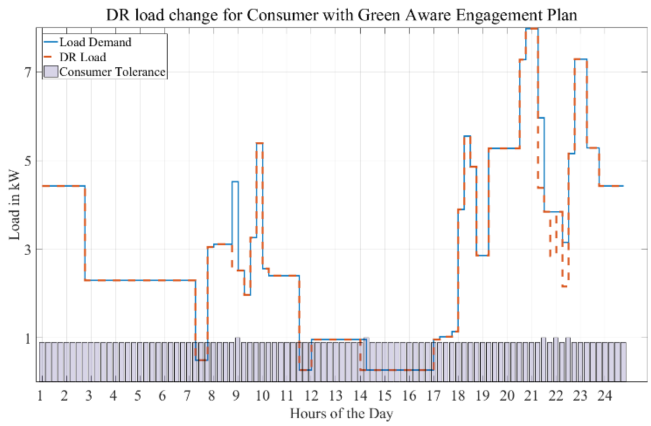

Fig 4. MILP-DR for Green Aware engagement plan

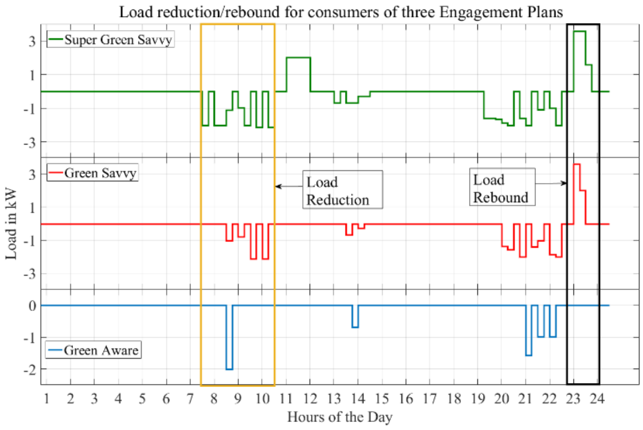

Fig 5. Load reduction/rebound for consumers with 3 engagement plans

TABLE III. TOTAL LOAD AND DR LOAD WITH AND WITHOUT MILP-DR

Method/Load	**MILP-DR with consumer tolerance factor**	**MILP-DR without consumer tolerance factor**
Tot. load demand	5090kWh	5090 kWh
Tot. Load Allowed using DR	4871 kWh	4797 kWh
Load Reduction during DR	356 kWh	431 kWh
Load reduction after time shifting Loads	219 kWh	293 kWh

IV. CONCLUSION

The presented work investigates the impact of consumer tolerance towards the performance of a DR program. Four tolerance-based consumer engagement plans are defined, according to which the load reduction request is distributed. The two stage algorithm was effectively able to regulate the load reduction distribution without overburdening the consumers to achieve it. It was also able to account for the demand redistribution to off-peak periods to fulfil consumer demand. Compared to MILP-DR with consumer tolerance minimization, the normal load reduction algorithm was able to reduce a higher amount of load, which directly showcases the capability of the proposed algorithm when considering consumer inconvenience over the economic benefits of load reduction alone. The proposed algorithm, in conjunction with fast and reliable communication channel, can work in tandem with a home automation system, thereby increasing the energy efficiency within a domestic environment.

REFERENCES

[1] A. Naeem, A. Shabbir, N. Ul Hassan, C. Yuen, A. Ahmad, and W. Tushar, "Understanding customer behavior in multi-tier demand response management program," *IEEE Access*, vol. 3, pp. 2613–2625, 2015.

[2] C. V. Chandran and K. Sunderland, "Comparative Study between Direct Load Control and Fuzzy Logic Control Based Demand Response," 2016.

[3] N. U. Hassan *et al.*, "Framework for minimum user participation rate determination to achieve specific demand response management objectives in residential smart grids," *Int. J. Electr. Power Energy Syst.*, vol. 74, pp. 91–103, 2016.

[4] N. Ul Hassan, Y. I. Khalid, C. Yuen, and W. Tushar, "Customer engagement plans for peak load reduction in residential smart grids," *IEEE Trans. Smart Grid*, vol. 6, no. 6, pp. 3029–3041, 2015.

[5] "European Commission - Press release - Commission welcomes political agreement on conclusion of the Clean Energy for All Europeans package." [Online]. Available: http://europa.eu/rapid/press-release_IP-18-6870_en.htm. [Accessed: 18-May-2019].

[6] M. H. Yaghmaee, A. Leon-Garcia, and M. Moghaddassian, "On the Performance of Distributed and Cloud-Based Demand Response in Smart Grid," *IEEE Trans. Smart Grid*, vol. 9, no. 5, pp. 5403–5417, Sep. 2018.

[7] C. Li, X. Yu, W. Yu, G. Chen, and J. Wang, "Efficient Computation for Sparse Load Shifting in Demand Side Management," *IEEE Trans. Smart Grid*, vol. 8, no. 1, pp. 250–261, Jan. 2017.

[8] P. Palensky and D. Dietrich, "Demand Side Management: Demand Response, Intelligent Energy Systems, and Smart Loads," *IEEE Trans. Ind. Informatics*, vol. 7, no. 3, pp. 381–388, Aug. 2011.

[9] A. R. Jordehi, "Optimisation of demand response in electric power systems, a review," *Renew. Sustain. Energy Rev.*, vol. 103, no. September 2017, pp. 308–319, 2019.

[10] S. H. Madaeni and R. Sioshansi, "Using demand response to improve the emission benefits of wind," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 1385–1394, 2013.

[11] S. Shao, M. Pipattanasomporn, and S. Rahman, "Grid integration of electric vehicles and demand response with customer choice," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 543–550, 2012.

[12] Y. Guo *et al.*, "Machine learning-based thermal response time ahead energy demand prediction for building heating systems," *Appl. Energy*, vol. 221, pp. 16–27, 2018.

[13] J. R. Vázquez-Canteli and Z. Nagy, "Reinforcement learning for demand response: A review of algorithms and modeling techniques," *Appl. Energy*, vol. 235, pp. 1072–1089, Feb. 2019.

[14] C. Chen, J. Wang, Y. Heo, and S. Kishore, "MPC-based appliance scheduling for residential building energy management controller," *IEEE Trans. Smart Grid*, vol. 4, no. 3, pp. 1401–1410, 2013.

[15] S. Li, D. Zhang, A. B. Roget, and Z. O'Neill, "Integrating home energy simulation and dynamic electricity price for demand response study," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 779–788, 2014.

[16] K. Dehghanpour, M. Hashem Nehrir, J. W. Sheppard, and N. C. Kelly, "Agent-Based Modeling of Retail Electrical Energy Markets with Demand Response," *IEEE Trans. Smart Grid*, vol. 9, no. 4, pp. 3465–3475, 2018.

[17] A. Nikoobakht, J. Aghaei, M. Shafie-Khah, and J. P. S. Catalão, "Assessing Increased Flexibility of Energy Storage and Demand Response to Accommodate a High Penetration of Renewable Energy Sources," *IEEE Trans. Sustain. Energy*, vol. 10, no. 2, pp. 659–669, 2019.