KPI for Managing and Controlling a Demand Response System: A Testing Framework for End Users

Débora de São José, Pedro Faria, Cátia Silva
GECAD – Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development
Porto, Portugal

Zita Vale
Polytechnic of Porto
Porto, Portugal
zav@isep.ipp.pt

Abstract — **Considering the increase of distributed generation and the complexity in power electricity management, demand response programs can be a way to reduce stress and strengthen power grids. However, as demand response involves end users changing their consumption patterns and adapting to on time different scenarios, some decision-making support tools are necessary. The present paper proposes and tests an energy management and controlling framework to assist electricity end users in decision making in a demand response scenario while using a set of key performance indicators. The tool was tested using a group of 20 end users and showed a consistent result throughout all the elements in the consumers group, total consumption presented a small decrease due to reduce of comfort, especially during weekdays.**

Index Terms-- **Demand Response, Key Performance Indicators, KPI, Monitoring, System Management**

I. Introduction

Distributed generation is seen as a new trend, from residential apartments and commercial buildings in urban centers to remote/isolated rural areas. There are many reasons for its implementation, in some cases, it came as a way to reduce energy costs, to mitigate climate change and to reduce peak consumption, in other cases, it came as the most efficient and least cost solution to bring electricity to more remote areas, sparsely populated and difficult to access.

Based on that, distribute generation is considered a necessary path to increase renewable generation and also to reduce losses, costs and inefficiencies in the energy sector [1].

Distributed energy generation differ from the traditional one, which is composed of centralized big power plants, far from the consumption centers which generate energy to a large group of passive consumers. With distributed generation, the consumer is active (as it is also a producer and named a prosumer), the energy is generated in small proportions to self-consumption or to supply a small group of consumers, who are localized near the producer.

Thus, to transition the power system from a traditional one to another with participation of distributed generation, a new model is being implemented, the well know smart grid.

Smart grid is defined as “a generation, transmission and distribution system equipped with a two-way communication system controlled by the grid operator” [1] and has the purpose of reduce stress and strengthen the power grid. There are many ways of achieving that, including balancing supply and demand and avoid overload the power grid.

Therefore, the collaboration with consumers by using their flexibility to change consumption pattern from peak periods to periods with less demand is vital. That change can be achieved through Demand Response (DR) programs, where consumers can change their demand as a response to an external signal.

So, in order to do this is necessary to access the performance and have immediate feedback. Based on that, key performance indicators (KPI), as the name suggests, a group of the most significant variables to be measured when one aim to access the success of a strategy or a management process, which means, the effectivity to reach the expected goals, was analyzed as a tool for managing and controlling a demand response system as it can lead to a faster and more focused analysis as it provide on time graphical information, which results on faster analysis and decision making, with lower margin for error or miss understandings.

In that context, a managing and controlling tool is proposed and tested in the present paper to help evaluating end users’ performance and facilitate the decision-making process. The creation and testing of a tool were thought to support electricity end users to make decision and change consumption pattern in a DR scenario while using a simple, visual and effective method, KPI.

This paper is organized in five sections: (1) introduction; (2) a concise literature review; (3) methodology; (4) results and discussion; and (5) the conclusions of this study.

II. Literature Review

Demand response is defined by [2] as changes performed by end-user electricity consumers that occur as consequence

This work has received funding from FEDER Funds through COMPETE program and from National Funds through (FCT) under the projects UIDB/00760/2020 and COLORS PTDC/EEI-EEE/28967/2017, and grants CEECIND/02887/2017 and SFRH/BD/144200/2019.

of (1) changes in electricity prices over time; or (2) decrease in electricity consumption as a result of incentive payments.

Thus, DR can be defined as end users intentionally changing their consumption patter (period of the day, instantaneous demand or total consumption). [2] presents three general actions that cause such change:

- Same consumption during off-peak periods and small consumption during peak periods: higher prices during peak time and implies temporary reduction of comfort;
- Shifting demand from peak to off-peak periods: there is no loss of comfort and, for residential customers, there is no cost in the action;
- Generating completely or partially their own energy: none or little change in previous consume pattern.

Based on that, consumers can change their behavior and consumption by reducing their comfort, which can be associated with a gain that compensate the comfort loss; shifting their demand, which is associated with a change in habits/routine/schedule; or by starting to generate their own energy, (total or partially) which means some investment and conditions (structure, geography, among others) that may not be available.

Furthermore, as DR implies an intentional change that consumers make in their own behavior in order to reduce or adapt electricity use, and considering that this change can happen in different ways as presented, it is necessary some measurements to analyze the results of the DR program, i.e. how the consumers are willing to change their behavior.

In order to help final consumers to make better-informed decisions to change their consumption pattern and helping balance demand and supply, reduce the stress of the grid and reduce their own costs, a set of KPI was created to work as an energy management and controlling tool. KPI are a visual/graphic management tool that allow clear and fast asses to information, reduce the response time and increase its number and effectivity.

Furthermore, KPI have already been used in some projects to assess energy efficiency in smart grid scenarios ([3]; [4]; [5]; [6]; [7]) and it is proven to be a reliable toolt provides decision support to stakeholders. However, the cited authors do not evaluate the type of response action chosen by the consumers and some of them just present and explain the KPI method without testing it with any group of real consumers.

Knowing that the goal of this research is to create and test a managing and controlling tool for end users to assist in decision making their decision in a DR scenario, analyze their predominant type of change and test it with a group of real end-users was fundamental for the success of this research.

III. Methodology

This work is preceded by [8] research on aggregation's influence on final remuneration of the resources associated with virtual power player. In such work, the consumers are aggregated according to their actual participation in Demand response events, so it is possible to achieve a number of tariff groups for the remuneration of the demand reduction provided.

The goal of the proposed methodology in the present paper is to create and test an energy management and controlling tool to assist electricity end users to make their decision to change consumption pattern in a DR scenario with the support of a selected KPI group. In order to build and test the tool, data from 20 consumers were taken. The data comes from a Virtual Power Player and all 20 elements from the sample are only consumers (do not generate energy) of Incentive-based Demand Response Program. That means the only response actions available are to reduce electricity consumption or to shift the original demand. Furthermore, it used two periods of analysis, the first one corresponds to the consumption before DR implementation and the second one, after implementation.

Considering the interactions between this research and [8], Figure 1 presents the overview of the proposed methodology.

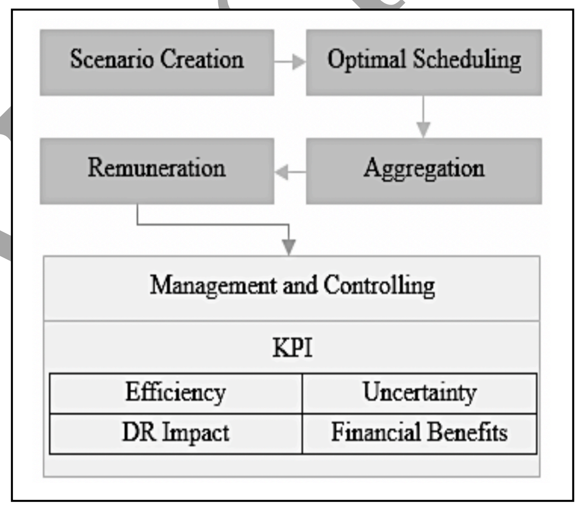

Figure 1: Overview on proposed methodology

For this research, it was used the original database from [9] which had its dimension adapted considering research purposes (not all consumers were considered for testing this methodology, although the selection was random).

Based on that, a group of 20 consumers were subjected to a management and controlling framework with a group of KPI presented as follow.

Furthermore, the KPI, as it intends to measure the performance of each demand response goal and show if the current strategy is bringing the expected results and access how the variables are evolving, so, in order to do that the following topics were analyzed: (1) Volume of energy consumption in higher prices; (2) Volume of energy consumption is lower prices; (3) Homogeneity of consumers; (4) Daily price curve; and (5) Consumers that better adapt their consumption considering the expected changes.

In order to access the homogeneity of the group it was also necessary to measure the DR impact, which means, the response rate of consumers after implementing DR.

DR Impact measures end users changes due to demand response programs. In this group of interest, the before consumption is measured before DR implementations and after consumptions is measured after its implementation. It was used three formulas to access this change, which were previously used and can be seen in [3] and [10].

The first one is Change in Total Consumption and can be defined as the change considering the periods before (orig.consumption) and after (new.consumption) implementation.

$$\frac{orig.consumption - new.consumption}{orig.consumption} \tag{1}$$

The second, Change in Consumption during Peak Periods corresponds to the consumption between 8:00 hours and 22:00 hours, considering the periods before (orig.peak.consumption) and after (new.peak.consumption) implementation.

$$\frac{orig.peak.consumption - new.peak.consumption}{orig.peak.consumption} \tag{2}$$

And Change in Consumption during Off-Peak Periods correspond to all periods that were excluded in the previous equation, also analysing periods before (orig.offpeak.consumption) and after (new.offpeak.consumption) implementation.

$$\frac{orig.offpeak.consumption - new.offpeak.consumption}{orig.offpeak.consumption} \tag{3}$$

The last equation in DR Impact group is Customer Response Action, which measures the change in consumption per period comparing the periods before and after DR implementation and return the more frequent behaviour of each consumer, comfort loss (decrease in total energy consumption) or demand shift (decrease in energy consumption during a period of the day with no or minimal change in consumption considering the entire day). The results obtained during the test analysis can be found in section IV.

IV. Results and Discussion

A group of 20 consumers were subjected to a management and controlling framework with a group of KPI presented in section 3. The sample data were collected with a time interval of 15 minutes and, for the analysis, were used four time frames, Weekdays, Saturday, Sunday and Whole Week, this difference is due to costs variability, as during Sundays there is no difference in electricity price through the day, and on Saturdays this variability is less frequent than the one during weekdays.

Furthermore, all of the sample elements are domestic consumers who does generate neither part nor total electricity they consume. It was considered the prices and time periods used in [8] and it was, also, considered two periods, one before (January/2018) and one after (February/2018) implementation, for comparison. When analysing change in patters, the first 3 days of January were ignored, so both periods would have the same length and start in the same weekday.

Figure 1 presents the daily price curve to which the consumers were subject to during the periods of January and February 2018.

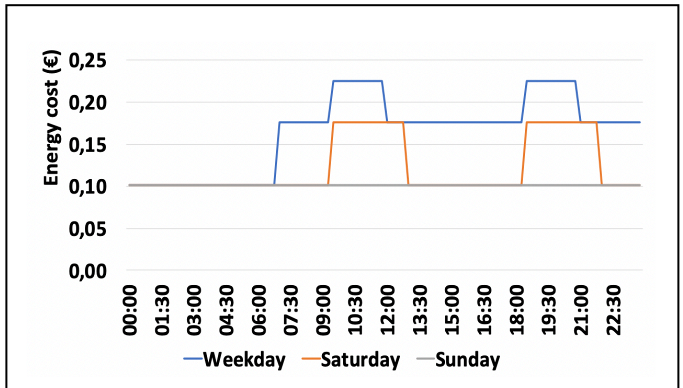

Figure 2: Price curve

Note that, between midnight and 07:00 a.m. there is no price difference in the three periods. The highest consumption periods start and ends few minutes later on Saturday when compared to weekdays, and also has a longer duration.

Considering 3 different periods, low price (0,1016 €), medium price (0,1765 €) and high price (0,2253 €), Figure 3 shows the total consumption of a random consumer from the selected group and for the total group (energy community) during the studied time.

From Figure 3 one can notice that the consumption had a small decrease in the second month (period with demand response) during all the analyzed periods and that all elements of the group has a very similar consumption pattern (similar demand curve), which shows some homogeneity in the group.

However, in order to measure how homogeneous the group is when responding to the system, Table 1 presents the total impact of demand response and Figure 4 presents the consumption curve for three consumers, when comparing the periods before and after implementation.

From Table 1, one can notice that all consumers presented a positive change due to DR impact, which means that all customers intentionally changed their consumption patter. However, in all cases their response was, predominantly, due to a loss in comfort and not a shift in demand. Another aspect that should be noticed is that the electricity consumption presented a decrease during both periods, peak (when the DR system send signals to the consumer to reduce their demand) and during off-peak periods (when the reduction was not necessary). To better understand that, a deeper analysis will be necessary.

Considering the members of the analysed group, the results were very uniform. All the members presented the same total change, however, when analysing the change during peak and off-peak periods, the consumer C18 is the one who got the most different result from the group presenting the least change in both situations.

TABLE I. TABLE 1: DR IMPACT

Consumer	Change in Consumption			Customer Predominant Response Action
	Total	*Peak*	*Off-Peak*	
C1	0,12	0,12	0,11	Comfort Reduction
C2	0,12	0,12	0,11	Comfort Reduction
C6	0,12	0,12	0,11	Comfort Reduction
C7	0,12	0,12	0,11	Comfort Reduction
C8	0,12	0,12	0,11	Comfort Reduction
C4	0,12	0,12	0,11	Comfort Reduction
C16	0,12	0,12	0,11	Comfort Reduction
C17	0,12	0,12	0,11	Comfort Reduction
C19	0,12	0,12	0,11	Comfort Reduction
C3	0,12	0,11	0,10	Comfort Reduction
C9	0,12	0,11	0,11	Comfort Reduction
C11	0,12	0,11	0,11	Comfort Reduction
C12	0,12	0,11	0,10	Comfort Reduction
C13	0,12	0,11	0,11	Comfort Reduction
C14	0,12	0,11	0,10	Comfort Reduction
C15	0,12	0,11	0,10	Comfort Reduction
C20	0,12	0,11	0,10	Comfort Reduction
C10	0,12	0,10	0,09	Comfort Reduction
C5	0,12	0,09	0,08	Comfort Reduction
C18	0,12	0,02	0,02	Comfort Reduction
Community	0,12	0,12	0,11	Comfort Reduction

From Figure 4 one can notice that C1 has a higher consumption curve when compared to the other two consumers in the figure (but not when compared to all the other consumers). C1 is also between the ones who presented the higher changes in consumption behaviour as presented in Table 1. The lower change in consumption presented by C8 may be explained by its consumption pattern, which is the smaller consumption considering the 20 consumers and almost do not have consumption peaks (biggest variation is between the period of time when we can consider as sleep time).

Moreover, the only period when we can notice a shifting in the demand is in C1 during weekdays, when there is a decrease in energy consumption during most of the day and an increase during and after, what can be assumed as, dinner time (this period is the one that presents the smallest variation in consumption patterns in general). However, the observed increase in consumption is not enough to consider "shifting the demand" as the customer predominant response action.

Furthermore, from Table 1, 9 out of 20 consumers had a very similar result and are in the top group consumers in what concerns changing their consumption behaviour. Figure 4 presents the minimum, maximum and opening for all the three periods considering all 20 consumers.

Figure 5 shows that C8 very distant from the other consumers, when considering DR impact rate, probably due to its singular characteristics already presented.

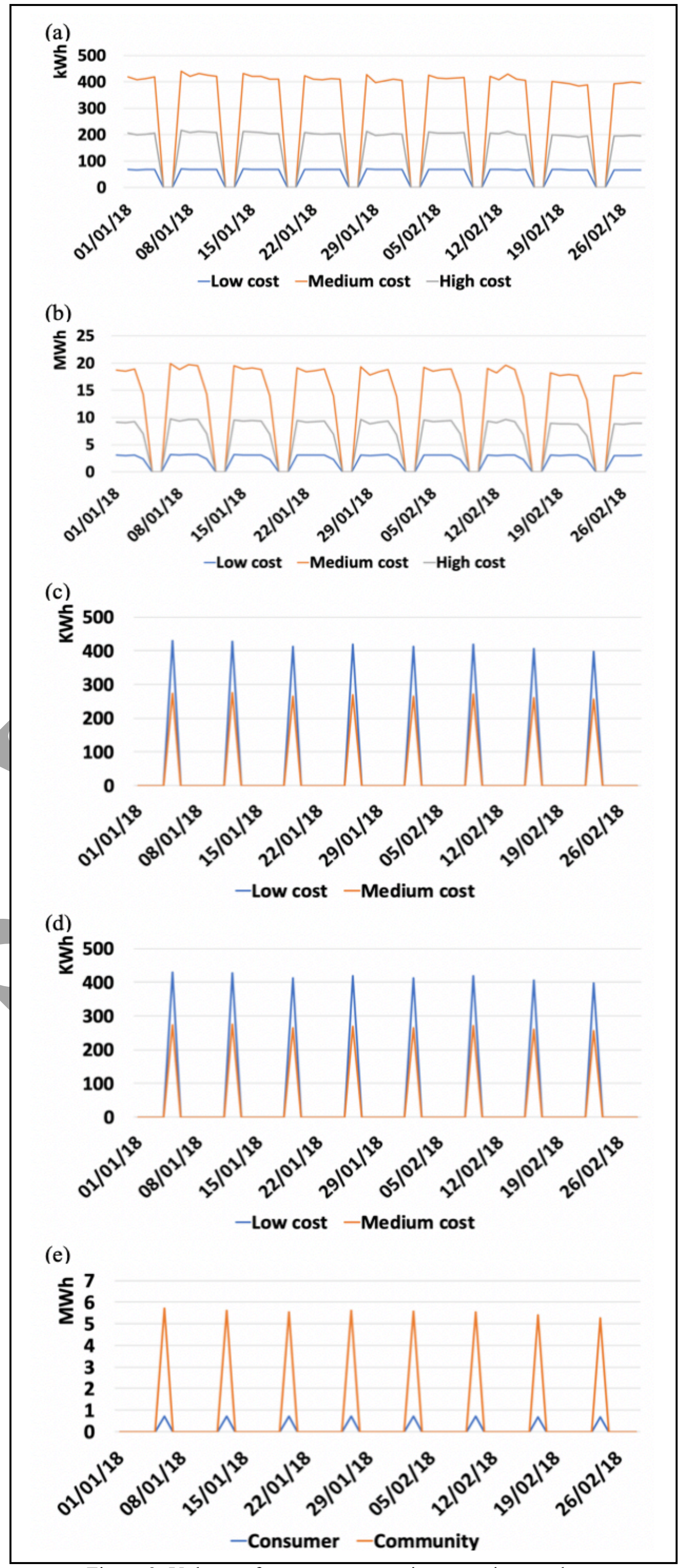

Figure 3: Volume of energy consumption per price per day

(a) and (b) randon consumer and community weekday consumption; (c) and (d) randon consumer and community Saturday consumption; (e) randon consumer and community Sunday consumption.

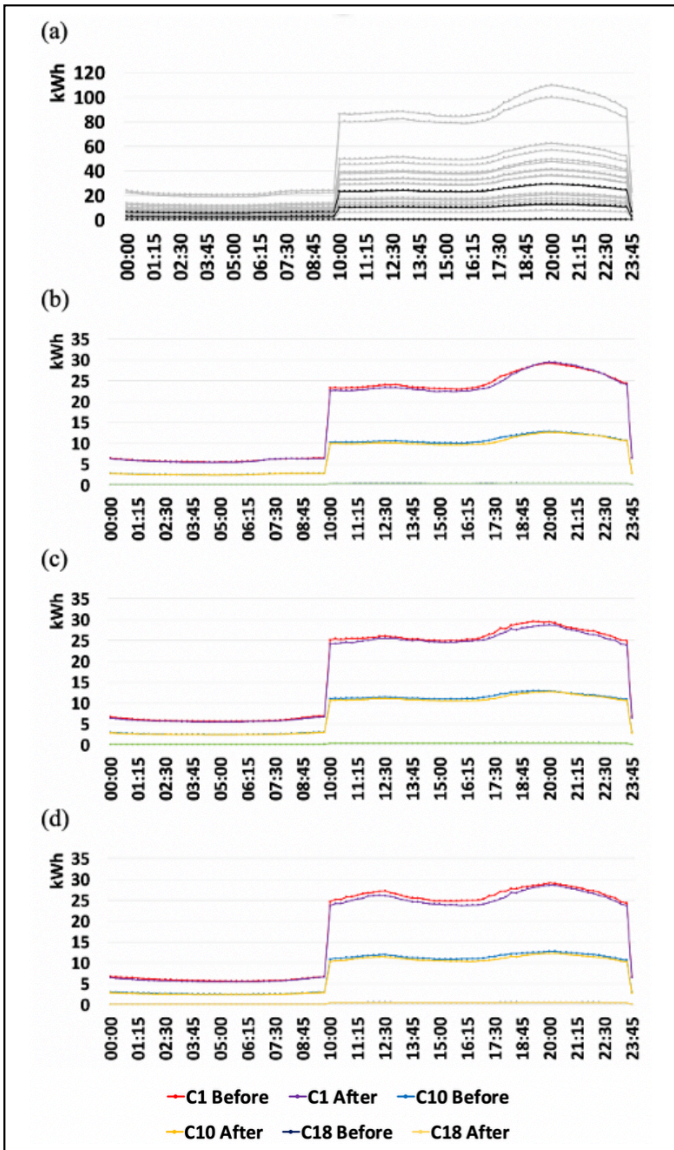

Figure 4: Consumption curve

(a) Consumption before implementation, all consumers with C1, C10 and C18 highlited in black;
Consumers C1, C10 and C18: (b) Weekday; (c) Sarurday; (d) Sunday.

The change in consumption due to implementation had it maximum values during weekdays, achieving 0,15 DR impact rate, and minimum in Sundays, when it achied values as low as 0,02 DR impact rate, even by members from the top group consumers

I. Conclusions

The goal of this study was to create and test an energy management and controlling framework to assist electricity end users to make decisions regarding to changing their consumption pattern in a DR scenario while using key performance indicators. The tool was tested using a group of 20 end users and showed a consistent result throughout all the elements in the sample. It presented a decrease in energy total energy consumption after DR implementation, especially due to decrease in comfort. However, a deeper analysis is necessary to better understand the price-demand behavior and its influence in persuading consumers to change their consumption pattern. Another subject for future research is to analyze the top consumers group, their pattern and behavior and answer why some succeed while others are below expectations.

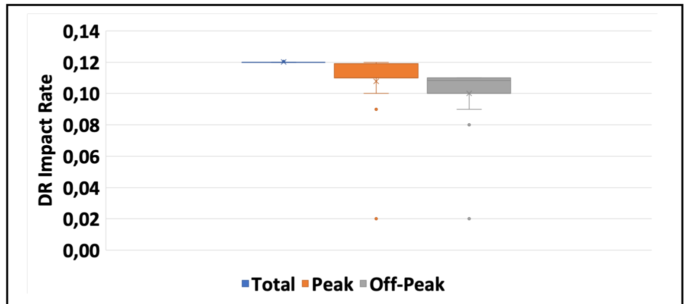

Figure 5: DR Impact change

References

[1] H. Mezouar, A. El Afia, & R. Chiheb, (2016). A new concept of intelligence in the electric power management. Proceedings of 2016 International Conference on Electrical and Information Technologies, ICEIT 2016, 28–35.

[2] M. Albadi, & E. El-Saadany (2008). A summary of demand response in electricity markets. Electric Power Systems Research, 78(11), 1989–1996.

[3] R. Fadhel Khelifa, & K. Jelassi, (2016). An energy monitoring and management system based on key performance indicators. IEEE International Conference on Emerging Technologies and Factory Automation, ETFA, 2016-Novem, 1–6.

[4] S. Hussain, H. Gabbar, F. Musharavati, & S. Pokharel, (2013). Key performance indicators (KPIs) for evaluation of energy conservation in buildings. IEEE International Conference on Smart Energy Grid Engineering, SEGE 2013, 1–6.

[5] G. May, M. Taisch, & D. Kelly, (2013). Enhanced energy management in manufacturing through systems integration. IECON Proceedings (Industrial Electronics Conference), 7525–7530.

[6] A. Rasam, F. Hanif, A. Samad, & R. Hadi, (2013). Spatial information management system for building energy consumption. Proceedings - 2013 IEEE 3rd International Conference on System Engineering and Technology, ICSET 2013, 295–299.

[7] R. Sanz, A. Corredera, J. Hernández, J. Samiengo, J. Vicente, & L. Bujedo, (2015). Towards the integration of monitoring systems to support the evaluation of nearly Zero Energy Buildings through Key Performance Indicators. 2015 IEEE Workshop on Environmental, Energy, and Structural Monitoring Systems, EESMS 2015 - Proceedings, 90–95.

[8] C. Silva, P. Faria, & Z. Vale (2019). Multi-period observation clustering for tariff definition in a weekly basis remuneration of demand response. Energies, 12(7).

[9] P. Faria, J. Spínola and Z. Vale, "Aggregation and Remuneration of Electricity Consumers and Producers for the Definition of Demand-Response Programs," in IEEE Transactions on Industrial Informatics, vol. 12, no. 3, pp. 952-961, June 2016, doi: 10.1109/TII.2016.2541542.

[10] G. Thanos, M. Minou, T. Ganu, V. Arya, D. Chakraborty, J. Van Deventer, & G. Stamoulis, (2013). Evaluating demand response programs by means of key performance indicators. 2013 5th International Conference on Communication Systems and Networks, COMSNETS 2013, 1–6.