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Research Article

Two-Stage Stochastic Optimization for Cost-Effective Energy Management in Grid-tied Microgrids

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Abstract:

Effective energy management is essential for minimizing operational costs in grid-connected microgrids (MGs), particularly as renewable energy sources such as solar photovoltaics and wind turbines are increasingly integrated into modern power systems. This paper presents a two-stage energy management strategy aimed at minimizing the total cost of a grid-connected MG. In the first stage, day-ahead scheduling, energy dispatch is optimized using stochastic optimization techniques while accounting for uncertainties in renewable generation and load demand. A Monte Carlo simulation generates multiple scenarios to assess future states, facilitating precise decision-making for grid interaction and local generation. As a result, the total operational cost is reduced from Rs. 12,521 to Rs. 12,390, and the total cost is reduced from Rs. 158,090 to Rs. 14,998. The second stage, real-time scheduling, refines the day-ahead plan by adjusting for real-time fluctuations in demand and generation, ensuring system balance and reliability. By integrating metaheuristic algorithms with real-time control, the proposed strategy minimizes energy exchange costs with the grid, reduces operational expenses of conventional generators, and maximizes the utilization of renewable energy. Case studies validate the effectiveness of the proposed methodology in reducing overall costs, maintaining grid stability, and enhancing renewable energy penetration. The method is adaptable to various MG configurations, offering a robust and cost-efficient solution for energy management in grid-connected systems.

1. Introduction

The transition from fossil fuels to clean energy has become imperative due to climate change and increasing energy demands driven by population growth. This shift necessitates the integration of renewable energy sources into microgrids (MGs) [1-3]. An MG is a small-scale energy system that can operate independently or in conjunction with the main grid to generate, distribute, and manage electricity efficiently [4-6]. It incorporates various distributed energy resources (DERs), including backup generators such as microturbines, diesel generators, and fuel cells, alongside renewable sources like solar photovoltaic (PV) panels, wind turbines (WTs), and battery energy storage systems (BESS) [7,8].

While renewable energy sources such as solar PV and WTs play a crucial role in MGs, their inherent intermittency introduces uncertainty, which must be mitigated through forecasting, energy storage, and backup generation. BESS are essential for storing surplus renewable energy and supplying power during periods of low renewable generation or when the MG operates in island mode. Diesel and gas generators serve as backup sources, particularly in islanded operation, but their higher operational costs make them less preferable compared to renewables and storage solutions [9,10].

In grid-connected mode, the MG is linked to the main utility grid, allowing bidirectional power flow. This enables the MG to either import power during periods of insufficient local generation or export excess energy back to the grid. This operational flexibility facilitates cost minimization and enhances renewable energy utilization. Conversely, in islanded mode, the MG operates independently from the main grid, necessitating a real-time balance between local generation and demand to ensure reliability and stability. Since there is no external power support, BESS play a pivotal role in managing energy imbalances, preventing overloading, and mitigating blackouts [11-13]. Renewable energy systems has been studied and reported in literature [14-16].

Seamless transitioning between grid-connected and islanded modes is critical for ensuring uninterrupted power supply. This requires advanced control systems capable of detecting grid disturbances and implementing appropriate switching strategies without disrupting power delivery to connected loads. Scheduling algorithms for MG operations typically aim to optimize economic returns, minimize environmental impact, and reduce overall operational costs [17,18]. These scheduling problems can be addressed through various optimization techniques, including single-objective, multi-objective, linear, non-linear, integer linear, mixed-integer linear, and mixed-integer non-linear programming approaches. Additionally, scheduling methodologies may follow single-stage or two-stage optimization frameworks. The on/off nature of load scheduling introduces non-convexity into the objective function, further complicating the optimization process. Figure 1 illustrates the dispatchable and non-dispatchable energy sources in an MG.

To enhance MG efficiency, several optimization techniques are employed, broadly categorized into deterministic, stochastic, and heuristic/metaheuristic approaches [19-21]. Deterministic methods rely on precise inputs and yield well-defined outputs under a given set of constraints. In contrast, stochastic optimization techniques incorporate uncertainties in renewable energy generation, load demand, and market conditions, making them particularly suitable for managing the variability associated with solar and wind energy. Heuristic and metaheuristic algorithms are often utilized for solving complex, non-linear optimization problems in MGs where traditional methods may struggle. While these approaches do not guarantee a globally optimal solution, they are highly effective in identifying near-optimal solutions within large problem spaces.

BESS plays a crucial role in ensuring smooth transitions between grid-connected and islanded modes. In the event of a grid disturbance or outage, BESS can provide instantaneous energy supply to critical loads, enabling a seamless shift to islanded operation without service disruption.

This paper proposes an energy management framework that addresses these challenges by employing stochastic optimization techniques. The proposed methodology focuses on scheduling MG operations under uncertain renewable generation and load demand conditions, with the objective of minimizing total operational costs while ensuring system reliability and maximizing renewable energy penetration.

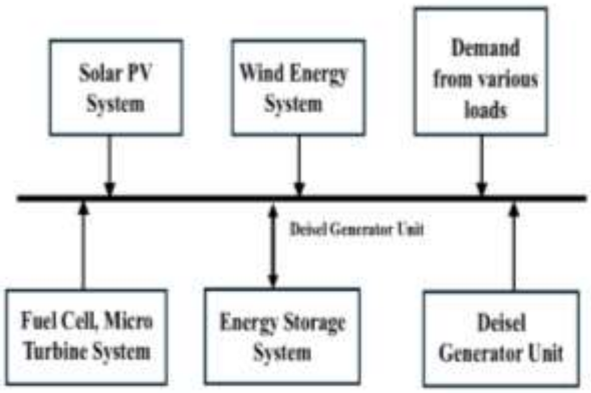

Figure 1. *Components of a typical Microgrid.*

2. Modeling

In MG systems, energy sources are typically clustered into dispatchable and non-dispatchable types based on their capability to be controlled and adjusted to meet demand. Understanding this distinction is crucial for optimizing energy management and preserving grid stability.

Dispatchable Energy Sources

Dispatchable energy sources can be controlled and regulated by grid operators to meet load demand.

These sources are flexible, denotation they can increase or decrease their output as needed, leaving for a reliable balance between supply and demand.

$$C_{Gr1}^{t} = a_0(P_{Gr1}^{t})^2 + a_1 P_{Gr1}^{t} + a_2 \quad (1)$$
$$C_{Gr2}^{t} = b_0(P_{Gr2}^{t})^2 + b_1 P_{Gr2}^{t} + b_2 \quad (2)$$
$$C_{Gr3}^{t} = c_0(P_{Gr3}^{t})^2 + c_1 P_{Gr3}^{t} + c_2 \quad (3)$$
$$C_{DS}^{t} = C_{Gr1}^{t} + C_{Gr2}^{t} + C_{Gr3}^{t} \quad (4)$$

Non-Dispatchable Energy Sources

Non-dispatchable energy sources produce power based on environmental conditions, which cannot be controlled by grid operators. Their output is irregular and reliant on factors like weather, making them less reliable for constant energy supply.

Photovoltaic system*s*

PV solar panels convert sunlight into electricity and are classified as an uncontrollable energy source. The output of solar PV systems is determined by solar irradiance, which varies based on time of day, weather conditions, and geographical location.

Wind turbines

Wind turbines generate electricity by harnessing wind energy, making them another uncontrollable source. Like solar PV, wind energy production is subject to environmental conditions in specifically wind speed and direction. Wind power can be highly variable, depending on local wind patterns, seasonal changes, and weather conditions.

3. Formation of Objective Functions

This section deliberates about the objective formulation in which the objective is to minimize the total cost of the MG. Eq. (10) specifies the energy balance equation of the MG and Eq. (5-9) signifies inequality constraint of the MG. It is essential to optimize the economic dispatch of dispatchable sources by relating real-time energy prices and MG operational cost by satisfying the constraints.

Inequality constraints

The constraints on the power generation i.e., lower and upper limits on generator outputs and battery charge and discharge limits are limited by inequality constraints. P_{PV}^{t}, P_{WT}^{t} indicates the generated output from PV and wind at time 't' respectively.

$$0 \le P_{PV}^{t} \le P_{PV}^{t,max} \quad (5)$$
$$0 \le P_{WT}^{t} \le P_{WT}^{t,max} \quad (6)$$
$$P_{DGr1}^{t,min} \le P_{DGr1}^{t} \le P_{DGr1}^{t,max} \quad (7)$$
$$P_{DGr2}^{t,min} \le P_{DGr2}^{t} \le P_{DGr2}^{t,max} \quad (8)$$
$$P_{DGr3}^{t,min} \le P_{DGr3}^{t} \le P_{DGr3}^{t,max} \quad (9)$$

A. Equality constraints

The generation, energy exchange should match the load demand which is governed by equality constraint as shown in Eq. (10).

$$P_{PV}^{t} + P_{WT}^{t} + P_{Gr1}^{t} + P_{Gr2}^{t} + P_{Gr3}^{t} \pm P_{BESS}^{t} \pm E_{Exch}^{t} = P_{load}^{t} \quad (10)$$
$$E_{Exch}^{t} = P_{Gen}^{t} - P_{load}^{t} \quad (11)$$

C_{DS}^{t} indicates the operational cost of the dispatchable sources and P_{Gr1}^{t} is the power generation from generator 1, a_0, a_1 and a_2 indicates the cost coefficients of generator 1. P_{Gen}^{t}, P_{load}^{t} indicates the generation and load demand at time 't' respectively. Eq. (11) indicates the amount of energy exchange with the utility grid.

Cost savings can be accomplished by storing energy, which assists in smoothing out variations in energy generation and utilization. Energy storage is used to store extra energy during off-peak hours and release it during peak usage.

$$SOC_{BESS}^{t,min} \le SOC_{BESS}^{t} \le SOC_{BESS}^{t,max} \quad 12)$$
$$SOC_{BESS}^{t} = SOC_{BESS}^{t-1} + \beta_{charge} P_{BESS}^{t-1} + \frac{1}{\beta_{discharge}} P_{BESS}^{t-1} \quad (13)$$

Eq. (12) and Eq. (13) indicate the limits on state of charge of the battery and state of charge in the current hour respectively.

$$CE_{Exch}^{t} = E_{Exch}^{t} * EP_{Grid}^{t} \quad (14)$$
$$TC = C_{DS}^{t} \pm CE_{Exch}^{t} \quad (15)$$

Day-Ahead Scheduling

This includes optimizing the energy resources of the MG based on predicted data for load demand, renewable generation (PV and WT), and grid circumstances. The objective is to optimize the operational costs which includes fuel costs for generators, power exchange costs with the grid, and start-up costs for non-renewable generators. Scenario generation using Monte Carlo simulation, is used to address uncertainties related to renewable energy generation.

- Read the DA forecast for load demand and renewable energy generation from PV and WT sources. Generate an initial population of candidate solutions. Each candidate signifies a potential energy dispatch solution for the MG over the DA period.
- Estimate whether the candidate solutions are within predefined operational limits, together with generation capacity, load demand, and

battery energy storage. If the solutions disturb any limitations, they are discarded or altered.

- For each feasible candidate solution, check whether the total generation (from renewable and diesel generators) meets or surpasses the load demand.

If generation ≥ load demand, the system proceeds with zero energy exchange between the MG and the grid.

If generation < load demand, energy exchange is desired. The grid supplements the deficit or the excess generation can be transferred to the grid.

- Calculate the day-ahead operational cost (OC) based on fuel cost of conventional generators such as diesel generators.
- Cost of energy exchange between the MG and the grid, considering both import and export costs based on the energy market price.

Real-Time Operation

In real time, the MG regulates its energy dispatch to match actual conditions, accounting for deviations in load demand and renewable output. Real-time energy management guarantees that the system remains balanced, evading power outages or excessive reliance on external resources.

4. Results and Discussions

The proposed two stage methodology was tested on an IEEE-33 bus system that comprises of 3 DG's, I WT and 1 PV source. Table 1 indicates the operational limits and cost functions of all the generators. Table 2 indicates the BESS charge and discharge characteristics and its efficiencies.

Figure 2 indicates the load demand on the IEEE-33 bus system, the amount of wind power generation and the amount of PV power generation. From the Figure 2 it is evident that the PV is having zero power output in the early hours of the day and during nights. However, the power of wind is available all the time. Figure 3 indicates the grid price and the MG price.

Figure 4 indicates the energy exchange with the grid and MG. It also specifies the amount of charge and discharge powers of BESS. Moreover, it also specifies the amount of energy exchange with the grid. Figure 5 indicates the dispatch schedule of the diesel generators.

From the Figure 5, it is clear that the generator 2 is scheduled last after scheduling 1 and 2. Since the incremental fuel cost characteristics of this generator is the highest. Therefore, it was scheduled at last. Figure 6 represents the operational cost characteristics of diesel generators.

Table 1. *Cost Coefficients and Limit of Generation.*

Type	Generator parameters				
	Min. limit	Max. limit	a_0	a_2	a_1
DGr. 1	0	150	0.01	2	10
DGr. 2	0	120	0.02	3	8
DGr. 3	0	100	0.015	1	12
WT	0	270	-	-	-
PV	0	250	-	-	-

Table 2. *Battery Energy Storage System Parameters.*

BESS parameter	Limits
BESS rating	20kWh
Charge efficiency	90% or 0.9
discharge efficiency	90% or 0.9
Lower limit on SOC	20% or 0.2
Upper limit on SOC	80% or 0.8
Initial SOC	50% or 0.5

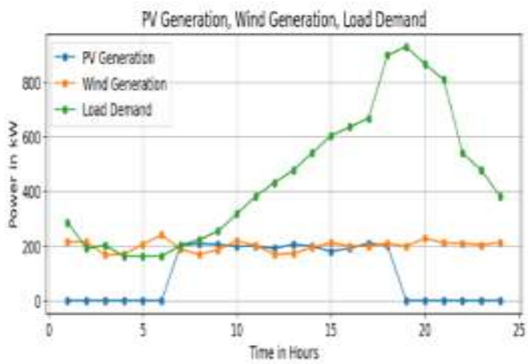

Figure 2. *Load demand and renewable energy power generation.*

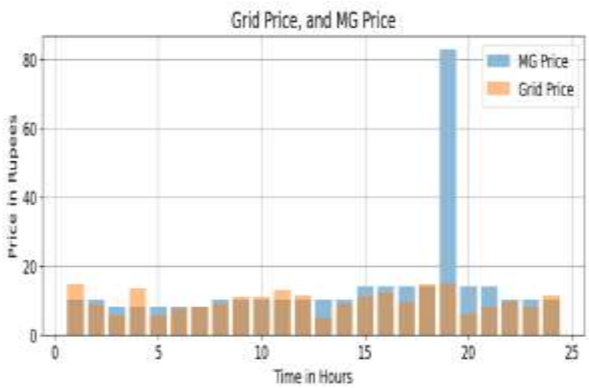

Figure 3. *Price of Grid and MG for 24-hours.*

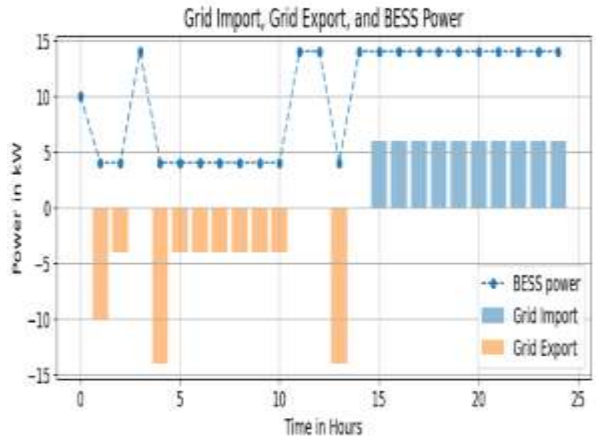

Figure 4. *Energy exchange between grid, MG and BESS.*

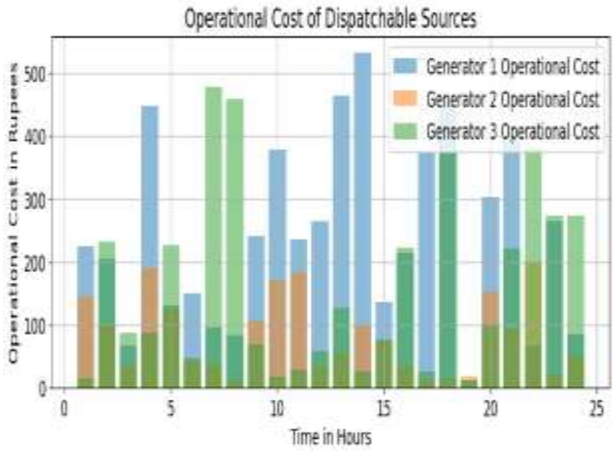

Figure 5. *Operational cost of the MG.*

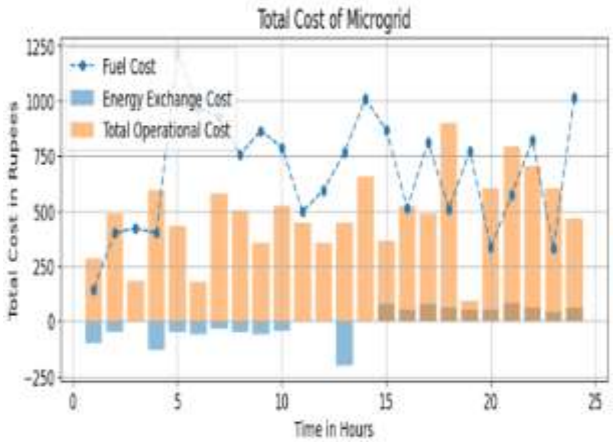

Figure 6. *Cost comparison of MG.*

4. Conclusion

This study proposes a comprehensive energy management approach for grid-connected MG's, intended at reducing total operational costs while maximizing the incorporation of renewable energy sources. The proposed two-stage framework, which combines day-ahead and real-time scheduling, addresses the inherent uncertainties behavior of renewable generation and load demand using stochastic optimization techniques. The day-ahead scheduling safeguards optimal energy dispatch by faking various future scenarios, while the real-time scheduling regulates the system in response to actual conditions, guaranteeing continuous reliability and cost-efficiency. The total operational cost is reduced to 0.93% and the total cost is reduced to 2.5%. Through case studies, the method validates its effectiveness in reducing operational and grid interaction costs, particularly by leveraging the elasticity of renewable resources like solar PV and wind turbines. The procedure augments grid stability reduces dependence on conventional generators and promotes sustainable energy use. Overall, this approach provides a viable solution for energy management in grid-connected MG s, offering scalability and adaptability for various operational environments. Future work may focus on incorporating advanced demand response programs and electric vehicle integration to further enhance cost savings and system flexibility.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

References

[1]. Uddin, M., Mo, H., Dong, D., Elsawah, S., Zhu, J., & Guerrero, J. M. (2023). Microgrids: A review, outstanding issues and future trends. *Energy Strategy Reviews, 49*, 101127. DOI: https://doi.org/10.1016/j.esr.2023.101127

[2]. Kumar, G. V. N., Sai, R. V., Reddy, T. M., S K Shajid, & Boora, K. (2024). Emulation of Wind Turbine System using fuzzy controller- based vector

Controlled Induction Motor Drive. *Journal of Modern Technology, 1*(1), 38-46

[3]. Abdulbaqi, A. S., Jassim, S. A. J., Sulaiman, B. H. S., Alsultan, Q. H. A., Abed, T. H. A., Panessai, I. Y., ... & Nejrs, S. M. N. (2023). Innovative control strategies for dynamic load management in smart grid techniques incorporating renewable energy sources. *Khwarizmia*, *2023*, 73-83. DOI: 10.70470/KHWARIZMIA/2023/007

[4]. Zhang, Y., & Su, Y. (2024). Towards a Sustainable Future: Exploring Innovative Financing Models for Renewable Energy. *MEDAAD*, *2024*, 34-40. DOI: 10.70470/MEDAAD/2024/006

[5]. Pagidela, Y., & Visali, N. (2024). A Short review on Optimal Allocation of Microgrid. *Journal of Modern Technology*, 132-140.

[6]. Uddin, M., Romlie, M. F., Abdullah, M. F., Abd Halim, S., & Kwang, T. C. (2018). A review on peak load shaving strategies. *Renewable and Sustainable Energy Reviews*, *82*, 3323-3332. DOI: https://doi.org/10.1016/j.rser.2017.10.056.

[7]. Conejo, A. J., Morales, J. M., & Baringo, L. (2010). Real-time demand response model. *IEEE Transactions on Smart Grid*, *1*(3), 236-242. DOI: 10.1109/TSG.2010.2078843

[8]. Bal, T., Ray, S., Sinha, N., Devarapalli, R., & Knypiński, Ł. (2023). Integrating Demand Response for Enhanced Load Frequency Control in Micro-Grids with Heating, Ventilation and Air-Conditioning Systems. *Energies*, *16*(15), 5767. https://doi.org/10.3390/en16155767

[9]. Shi, Q., Li, F., Hu, Q., & Wang, Z. (2018). Dynamic demand control for system frequency regulation: Concept review, algorithm comparison, and future vision. *Electric Power Systems Research*, *154*, 75-87. DOI: https://doi.org/10.1016/j.epsr.2017.07.021

[10]. Parvania, M., & Fotuhi-Firuzabad, M. (2010). Demand response scheduling by stochastic SCUC. *IEEE Transactions on smart grid*, *1*(1), 89-98. DOI: 10.1109/TSG.2010.2046430

[11]. Siano, P. (2014). Demand response and smart grids—A survey. *Renewable and sustainable energy reviews*, *30*, 461-478. DOI: https://doi.org/10.1016/j.rser.2013.10.022

[12]. Rahimi, F., & Ipakchi, A. (2010). Demand response as a market resource under the smart grid paradigm. *IEEE Transactions on smart grid*, *1*(1), 82-88. DOI: 10.1109/TSG.2010.2045906

[13]. G. V. Mrudul, Rohit. G, Harshavardhan. G, Dhanush. K, & Anudeep. B. (2024). Efficient Energy Management: Practical Tips for Household Electricity Conservation. *Journal of Modern Technology*, *1*(1), `1~8.

[14]. Akram M. Musa, Abu-Shaikha, M., & Al-Abed, R. Y. (2025). Enhancing Predictive Accuracy of Renewable Energy Systems and Sustainable Architectural Design Using PSO Algorithm. *International Journal of Computational and Experimental Science and Engineering,* 11(1). https://doi.org/10.22399/ijcesen.842

[15]. DAYIOĞLU, M., & ÜNAL, R. (2024). Comparison of Different Forecasting Techniques for Microgrid Load Based on Historical Load and Meteorological Data. *International Journal of Computational and Experimental Science and Engineering,* 10(4). https://doi.org/10.22399/ijcesen.238

[16]. DAYIOĞLU, M., & ÜNAL, R. (2024). Design and Economic Analysis of a Grid-Tied Microgrid Using Homer Software. *International Journal of Computational and Experimental Science and Engineering,* 10(3). https://doi.org/10.22399/ijcesen.239

[17]. Du, P., Lu, N., & Zhong, H. (2019). Demand response in smart grids (Vol. 262). *Cham: Springer International Publishing.* DOI: https://doi.org/10.1007/978-3-030-19769-8

[18]. Faria, P., Spínola, J., & Vale, Z. (2018). Distributed Energy Resources Scheduling and Aggregation in the Context of Demand Response Programs. *Energies*, *11*(8), 1987. https://doi.org/10.3390/en11081987

[19]. Sabri, M., Verde, R., Balzanella, A., Maturo, F., Tairi, H., Yahyaouy, A., & Riffi, J. (2024). A Novel Classification Algorithm Based on the Synergy Between Dynamic Clustering with Adaptive Distances and K-Nearest Neighbors. *Journal of Classification*, 1-25. DOI: https://doi.org/10.1007/s00357-024-09471-5

[20]. Chen, Y., Xu, P., Gu, J., Schmidt, F., & Li, W. (2018). Measures to improve energy demand flexibility in buildings for demand response (DR): A review. *Energy and buildings*, *177*, 125-139. DOI: https://doi.org/10.1016/j.enbuild.2018.08.003

[21]. Yan, X., Ozturk, Y., Hu, Z., & Song, Y. (2018). A review on price-driven residential demand response. *Renewable and Sustainable Energy Reviews*, *96*, 411-419. DOI: https://doi.org/10.1016/j.rser.2018.08.003