Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 31 No. 1 (2024)

Optimization and Statistical Analysis for an Independent Microgrid Operation through an Innovative Fusion of Demand Response Programs

Rekha Swami[1], Sunil Kumar Gupta[2]
[1]Research Scholar, Department of Electrical & Electronics Engineering, Poornima University, Jaipur, India,
[2]Professor, Department of Electrical & Electronics Engineering, Poornima University, Jaipur, India

Article History:

Received: *29-10-2023*

Revised: *12-12-2023*

Accepted: *28-12-2023*

Abstract:

Microgrid operations face increased difficulty due to the unpredictability of renewable energy sources, such as solar and wind. To address this challenge, energy storage devices are widely employed. Another method to enhance the safety and dependability of microgrids is the Demand Response Program (DRP), which lowers peak demand and shifts it to off-peak times.

In an effort to reduce overall operating expenses, this paper employs several DRPs to solve the Unit Commitment Economic Dispatch (UCED) problem for a self-sufficient microgrid. To enhance both the operation and financial effectiveness of the microgrid, a novel combination of DRPs is presented in this article. Ultimately, users will benefit from this combination.

The modeling of DRPs is based on consumer benefit and price elasticity models. The UCED issue is formulated and solved in GAMS using mixed-integer nonlinear programming (MINLP). The study demonstrates the proposed strategy on an 11-Bus Microgrid. According to optimization findings, operational expenses are reduced by 17.43%, 18.8%, 19.81%, and 14.3% with 0% load shedding when TOU-RTP-CPP-DLC DRPs are implemented.

In the DLC-DRP scenario, only consumers benefit. When compared to DLC-DRP alone, the suggested RTP+DLC-DRP combination decreases operational expenses by 15.93% and increases consumer advantages. Thus, both the microgrid operator and its users benefit from the proposed strategy.

Keywords: Independent microgrids, demand response programs, operating costs, load shedding, and elasticity are all related terms.

1. INTRODUCTION

Increasing power demand, decreasing fossil fuel supplies, and a smaller carbon footprint have put distributed generation (DG) ahead of traditional generating in today's world. Distributed generation (DG) encompasses both renewable and non-renewable energy sources, including solar, wind, and micro-turbines. Power quality, dependability, and decreased power losses are just a few of the many advantages of DGs. But they endanger the reliability of the electrical system [1]. One possible answer to these problems is microgrids. Distributed generators, an energy storage system, demand control, and a control unit make up microgrids, which are small power networks. Isolated modes allow them to function autonomously in the event of an emergency, even if they are normally connected to the wider grid [2-4]. An autonomous Microgrid has been the subject of recent study in terms of design, optimization, and simulation [5-6].

Microgrids use battery energy storage, generally in an independent mode, to manage renewable power output that is variable [7]. One alternative is to introduce the demand response program, which allows end users to adjust their energy usage in reaction to changes in power rates or incentives offered to reduce use during periods of high market pricing. By shifting power use from peak to off-peak hours, DRP lowers operational costs and keeps costly generators out of standby mode [8-9]. Price-based and incentive-based DRPs are the two main types of DRPs. Customers' power consumption habits shift in response to changes in energy pricing in price-based DRP, and in response to incentives offered to customers during peak hours in incentive-based DRP [10]. In [11], a price-elasticity-based DRP model is laid forth.

By performing unit commitment (UC), which determines the on/off state of generating units for the given demand, microgrid operation and economic efficiency are improved [12]. Economic dispatch (ED) then determines how much electricity to release from committed generators in order to meet the load demand while keeping operational expenses to a minimum. There has been a lot of research on using DRP in microgrid operations for UC and ED. According to Ref. [13], a price-based time-of-use (TOU) DRP is used to conduct dynamic economic dispatch. Without taking a 24-hour goal to lower operational expenses into account, [14–15] models an emergency DRP (EDRP) and a TOU DRP. In order to help customers, the real-time pricing (RTP) DRP models the decomposition approach to adjust power use in response to changing prices [16]. The effect of EDRP on microgrid dependability in the event of a generator outage was investigated in reference [17]. In order to reduce operational costs and transmission losses in grid-connected microgrids, a dual optimization approach was suggested in reference [18] that makes use of TOU and RTP DRPs. The goal of the stochastic optimization model put out in reference [19] was to increase the microgrid's dependability through the use of an incentive-based DRP while simultaneously optimizing the microgrid's profit.

In the day-ahead market, a new approach to implementing incentive-based DRP is suggested in [20]. The participants in this work are incentivized differently based on the hourly peak intensity, which sets it apart from its predecessor. Microgrid operations employ both price-based and incentive-based demand response methods [21]. In order to accomplish economic-emission dispatch in microgrid, the authors of reference [22] employed fuzzy self-adaptive particle swarm optimization, which outperformed PSO and Genetic Algorithm (GA). But DRP wasn't a part of the optimization model. Researchers have looked at the effects of varying customer numbers and installed wind capacity on key microgrid operating parameters [23]. In order to scale microgrids, several kinds of DRPs based on the exponential concept are employed in [24]. In [25], we find an incentive-based DRP model with an exponential function for managing the operations of a microgrid that is connected to the utility grid. This model aims to decrease operating expenses and pollution. In order to reduce the total operational cost of a grid-tied hybrid system using different microgrid components such as DR, EV, and battery, an efficient scheduling method is presented in reference [26].

Taking the demand forecasting inaccuracy into account, the authors of reference [27] devised a stochastic unit commitment model that minimizes the overall production cost for an independent microgrid. But the unpredictability of renewable power and DRP is ignored in this study. To schedule isolated microgrids into the future using an incentive-based DRP, the authors of reference [28] employed mixed-integer programming (MIP). Microgrid efficiency can be further improved by the authors' introduction of a cost model for vanadium redox batteries. By comparing the suggested model to GA, the authors affirm that it is superior. The optimization approach that lowers the prices of grid-purchased energy and DR implementation was developed by Ref. [29] using Mixed-Integer Linear Programming (MILP). To make the solar output predictable instead of uncertain, the authors apply the p-efficient approach. For EMS in microgrid planning, a two-level optimization method based on MILP and an enhanced Genetic Algorithm was described in reference [30]. The DR program is left out of the suggested paradigm. By adopting an incentive-based DRP utilizing AIMMS software, the daily running expenses of networked microgrids were reduced (Ref. [31]). But no one has looked at how various degrees of customer involvement in microgrid operations affect things. In [32], the authors proposed a bi-level scheduling approach that makes use of a real-time pricing DRP. Reducing operating expenses and user costs are the two overarching objectives. The authors improved upon the hybrid intelligence algorithm and the CPLEX solver with the addition of the interior point method to the Jaya algorithm, which they called Jaya-IPM. A grid-connected WT-PV-PAFC-MT-battery microgrid with stochastic energy and reserve scheduling was suggested in reference [33]. Using demand bidding, an auxiliary service market program, and TOU DRP, the authors simulated operational cost and emission reduction using differential evolutionary (DE) and modified PSO algorithms. The simulation was run for both deterministic and stochastic situations.

In [34], the authors detail how to use DRPs for power dispatch in both grid-connected and standalone microgrids, with the goal of lowering operating expenses, emissions, and power losses. The GAMS environment is used to solve the multi-objective optimization problem that is expressed using MILP. The use of fuzzy logic allows for the determination of battery charge and discharge. Various evolutionary algorithms, including PSO, GA, TS, and ABC, are simulated. It has been verified by the writers that the suggested approach surpasses. For economic-emission scheduling with TOU DRP, the new CSAJAYA algorithm (a hybrid of the Crow search and the JAYA algorithms) was suggested in reference [35]. The offered method outperforms the others because of its quick search and low standard deviation. In order to reduce operational expenses, the UC model is introduced in [36] for microgrids that incorporate renewable power generation. Prior to optimizing using the genetic algorithm, the author computed the initial population using an improved priority list (IPL) approach. In terms of reducing operating expenses, the proposed
solution outperforms PL alone. Nevertheless, DR integration into microgrid operation is not included in the suggested paradigm. An optimization model was suggested in Ref. [37] for the purpose of lowering the operational cost of a standalone microgrid that incorporates renewable energy sources such as solar, wind, battery storage, and demand response in addition to traditional power sources like coal, nuclear, and hydropower. The UC model was solved in GAMS using mixed-integer quadratically constrained programming, or MIQCP. The optimization result verifies that microgrids with DR installed consume less battery, which extends the life of the battery. Reference [38] presented a multi-objective optimization model to minimize operating cost and emissions using TOU DRP. A decentralized EMS was suggested in reference [39-42] as a means to lessen operational expenses in light of the uncertainties associated with load and renewable generation. In order to forecast wind speed, PV output, and overall energy usage, the author employed an ARMA model. In order to carry

out optimal generation scheduling, PSO is employed [39]. Reference [40] also included battery degradation cost in the operating cost of microgrid.

A review of the relevant literature reveals that DRPs have been put into place to address the UCED issue in microgrid operations, whether they are run independently or linked to the grid. These efforts aim to achieve various goals, including reducing operating costs and emissions while enhancing system dependability. Most of the previous research on microgrid optimization has relied on heuristic, evolutionary, or classical methods using either price-based (TOU, RTP, CPP) or incentive-based (DLC, EDRP, I/C, CAP) DRPs as the only metric. Although operational expenses are decreased in a price-based DRP, customers actually lose money when they participate, in contrast to an incentive-based DRP where consumers really gain something. Solving the UCED problem for a self-sufficient microgrid with a mix of price- and incentive-based demand response pricing (DRP) is, hence, the major objective of this paper. Based on findings from literature review, GAMS (General Algebraic Modeling System) outperform other evolutionary strategies and is hence recommended for solving optimization problems.

2. RESEARCH METHOD

2.1. Microgrid Configuration

In order to generate electricity, this paper takes into account an Independent Microgrid, which consists of a fuel cell, a wind turbine, a battery, and microturbines [26, 27]. All of the power sources in the microgrid under consideration have their capacities listed in Table I. The solar panels have a capacity of 25 KW and the wind turbines 15 KW.

Table 1. Installed Power Sources [22]

Power Sources	Minimum Power (KW)	Maximum Power (KW)	Bids (€ct/kWh)	Start-up/ Shutdown Cost (€ct)
Microturbine	6	30	0.457	0.96
Fuel cell	3	30	0.294	1.65
Photovoltaic	0	25	2.584	0
Wind turbine	0	15	1.073	0
Battery	-15	15	0.200	0

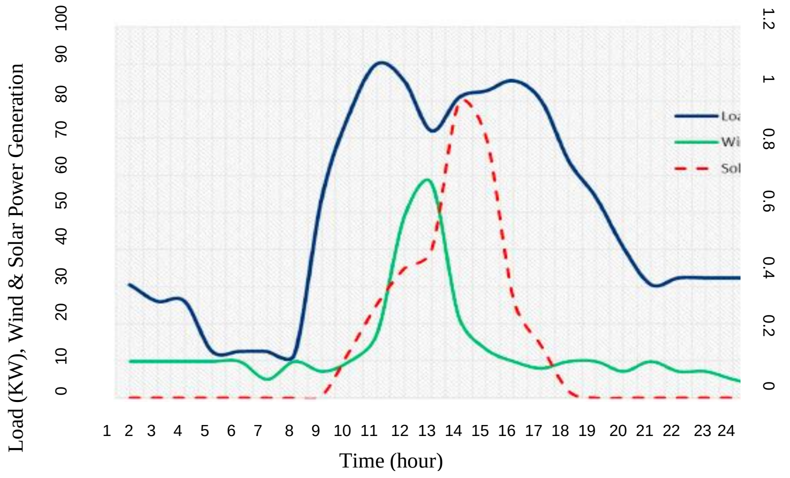

Figure 1. Estimated load curve and solar and wind power generation in p.u. of the 11-bus Microgrid [21,23]

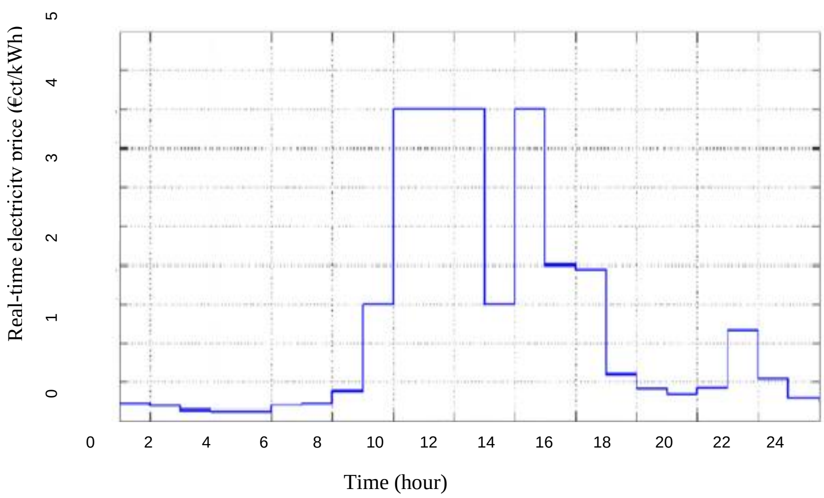

Figure 2. Real-time electricity prices [22]

For a whole day, the Microgrid, wind, and solar electricity production per unit demand is shown in 1. The peak load for the Microgrid on any given day is 90 KW, while the overall demand for the system is 1152 KW. Periods of low load (1–7 and 20–24), off-peak load (8 and 17–19), and peak load (9–16) make up the demand curve. For energy trading, Figure 2 shows the Microgrid's electricity pricing in real-time.

Microgrids rely on 30-kilowatt-hour batteries that are charged and discharged at rates of at least 15 kilowatts per second. The battery is initially set at 20 kWh and has a 95% efficiency rating for charging and discharging. Microgrid operators give customers a large payment known as the value of lost load (VOLL) in exchange for reducing their load during peak demand hours, which helps to improve operation security. The rising cost of running the microgrid is a direct result of VOLL. Thus, the goal is to lessen the frequency of load-shedding (LS). The average energy price of the Microgrid is 0.15 €ct/kWh, while the VOLL is 4 €ct/kWh. Twenty percent of microgrid users are expected to be actively involved in the DRP deployment. Table 2 shows how willing customers are to adopt DRP.

Table 2. Self and cross-elasticity of load [21,23]

	Low	Off-peak	Peak
Low	-0.10	0.032	0.024
Off-peak	0.032	-0.10	0.02
Peak	0.024	0.02	-0.10

2.2. DRP Modeling

As the price of electricity rises in the power market, demand for electricity falls and vice versa. Elasticity (E), defined as the demand's sensitivity to changes in the price of electricity, is used to represent this demand-price connection.

$$E = \frac{\text{Percent change in demand}}{\text{Percent change in price}} = \frac{\Delta q/q_0}{\Delta\rho/\rho_0}$$

$$E = \frac{\rho_0}{q_0}.\frac{\Delta q}{\Delta\rho} \qquad (1)$$

Where ρ_0 and q_0 are the initial cost of electricity ($/kWh) and initial demand (kW), $\Delta\rho$ the price change and Δq refers to the respective change in demand for this change in price.

In DRP, consumers reduce their demand during peak hours and shift it to off-peak hours due to these elasticities. The changed demand after implementing DRP is given by:

$$P_{L,DRP}(t) = P_L(t)\cdot\{1+E(t,t)\cdot\frac{[P(t)-P_0(t)+A(t)]}{P_0(t)} + \sum_{\substack{t'=1\\ t'\neq t}}^{24} E(t,t')\cdot\frac{[P(t')-P_0(t')+A(t')]}{P_0(t')} \qquad (2)$$

where $P_0(t)$-initial electricity prices, $P(t)$-spot electricity prices, A(t)-incentive given to consumers for DRP implementation, P_L-Demand before applying DRP, $P_{L,DRP}$-Changed demand after implementing DRP. In this equation, the second term is due to self-elasticity E(t,t), and the third term is due to cross-elasticity $E(t,t')$. DRP modeling in detail is provided in references [16-18-25-26-28].

2.3. Problem Formulation

2.3.1. Goal

We aim to lower the overall operating costs of the microgrid, which include the following terms: (1) fuel and startup/shutdown costs of generating sources; (2) operating costs of battery storage; (3) cost of energy not delivered to consumers; and (4) cost of implementing demand response pricing.

$$\text{Min } F = \sum_{t=1}^{T}\{\sum_{i=1}^{N_g}[P_{geni}(t)b_{gi}(t)u_i(t) + s_{gi}(u_i(t)-u_i(t-1))] + P_{esj}(t)b_{esj}(t) + \sum_{t=1}^{T} VOLL * ls(t) + \sum_{t=1}^{T} C_{DRP} \qquad (3)$$

Where T-total operating period of 24-hr (Δt=1h), N_g-number of generating units, u_i -status of unit i, P_{geni} *and* P_{esj} - output power of generating unit and battery storage, b_{gi} and b_{esj}-bids of generating unit and battery storage, S_{gi}-startup/shutdown costs of i[th] generating unit, LS -load shedding, VOLL-amount for energy not supplied and $C_{DRP}(t)$ -the cost of implementing DRP at time t.

2.3.2. Constraints

Demand-Supply balance

For the power system operation to be reliable, the power generated from the generating units, the battery (+ve when charging and –ve when discharging), and the load shedding should be equal to the load after implementing DRP.

$$\sum_{i=1}^{N_g} P_{geni}(t) + P_{esj}(t) + ls(t) = P_{L,\,DRP}(t) \tag{4}$$

Power production limit

The power output from generating units and the battery is controlled by their minimum and maximum limits.

$$P_{geni,Min}(t) * u_i(t) \le P_{geni}(t) \le P_{geni,Max}(t) * u_i(t) \tag{5}$$

$$P_{esj,Min}(t) \le P_{esj}(t) \le P_{esj,Max}(t) \tag{6}$$

Battery storage limits

Various battery constraints are given below:

The state of charge (soc) of the battery at any instant t is given by the soc at the previous interval, and the battery charge (P_c) and discharge power (P_d) multiplied by their respective efficiencies.

$$soc(t) = soc(t-1) + P_c(t)\eta_c - P_d(t)/\eta_d \tag{7}$$

Limits on soc are given by

$$soc_{Min}(t) \le soc(t) \le soc_{Max}(t) \tag{8}$$

The maximum charging and discharging power of the battery is limited.

$$P_{ch}(t) \le P_{ch,Max} \tag{9}$$

$$P_{dch}(t) \le P_{dch,Max} \tag{10}$$

Load Shedding

The shaded load by the Microgrid operator is provided by

$$0 \le LS(t) \le P_L \tag{11}$$

Mean (Average) of Operating Cost (12)

$$\text{Mean}_{\text{Operating Cost}} = \frac{\sum_{i=1}^{n} \text{Operating Cost}_i}{n}$$

Mode of Operating Cost

Mode Operating Cost = Value of Operating Cost with highest frequency (13)

Standard Deviation of Operating Cost (14)

$$\sigma_{\text{Operating Cost}} = \sqrt{\frac{\sum_{i=1}^{n} \left(\text{Operating Cost}_{i} - \text{Mean}_{\text{Operating Cost}} \right)^{2}}{n-1}}$$

Variance of Operating Cost (15)

$$\text{Variance Operating Cost} = \sigma_{\text{Operating Cost}}^{2}$$

Correlation Coefficient between Operating Cost and Consumers' Profit (16)

$$r_{\text{OC,CP}} = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}$$

Linear Regression Equation (Predicting Consumers' Profit based on Operating Cost) (17)

$$\hat{y} = \beta_0 + \beta_1 x$$

Slope (β_1) of Regression Line (18)

$$\beta_1 = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2}$$

Intercept (β_0) of Regression Line (19)

$$\beta_0 = \bar{y} - \beta_1 \bar{x}$$

Coefficient of Determination (R^2) (20)

$$R^2 = \left(r_{\text{OC,CP}}\right)^2$$

P-value for Testing the Significance of Slope (21)

$$\text{P-value} = P(T > |t|) \text{ where } t = \frac{\beta_1}{SE(\beta_1)}$$

Standard Error of the Slope $\left(SE(\beta_1)\right)$ (22)

$$SE(\beta_1) = \frac{\sigma_{\text{Operating Cost}}}{\sqrt{\sum (x_i - \bar{x})^2}}$$

Box Plot Outlier Calculation (for Operating Cost) (23)

$$\text{Outlier} > Q3 + 1.5 \times \text{IQR or Outlier} < Q1 - 1.5 \times \text{IQR}$$

Box Plot Outlier Calculation (for Operating Cost) (24)

$$\text{Outlier} > Q3 + 1.5 \times \text{IQR or Outlier} < Q1 - 1.5 \times \text{IQR}$$

Interquartile Range (IQR) for Operating Cost (25)

Mean Absolute Deviation (MAD) for Operating Cost

$$\mathrm{MAD}_{\text{Operating Cost}} = \frac{\sum_{i=1}^{n} \mid \text{Operating Cost}_{i} - \text{Mean}_{\text{Operating Cost}} \mid}{n}$$

3. RESULTS & DISCUSSION

This article presents a comparison and modeling of different DRPs in microgrid operation. We run our simulations under the assumption that all renewable power sources are fully operational. Use MINLP to formulate the system issue, and then solve it in GAMS.

3.1 With No DRP

Here, we run the simulation without DR to see whether we can reduce overall operating expenses to a minimum; the operational cost is 42,244 cents and the load shedding is 17.68 kWh.

Figure 3(a) shows that in the first few hours, the FC delivers the load because it bids cheaper. During peak hours, the MT unit begins to run in response to the increased load, and 86.53 kWh is discharged from the battery to meet the demand.

3.2. Time of Use (TOU) DRP

Rather of using a single tariff throughout the whole day, the costs are 5, 20, and 40 cents/kWh for low, off-peak, and peak load hours, respectively. With no load shedding, the whole operating cost comes to 35,931 cents. Due to the lack of customer incentives, DR is completely free.

Figure 3(b) shows that the FC unit runs during low load hours (1–7) because it bids lower, while the MT unit is mostly off. In order to meet the increased load requirement, the MT unit works with a discharge of 78.50 kWh from the battery. The cross-elasticity effect moves the 32.06 kWh demand to low and off-peak hours and reduces the load by 51.52 kWh during peak hours (9-16). Hours (8-19) see a decrease of 23.05 kWh due to self-elasticity of demand, whereas low-load hours see a shift of 3.83 kWh. A peak demand decrease of 10.13 KW is achieved in TOU-DR.

Table 3. Comparison among the existing and proposed work

Ref.	Mode	Objective Function	Price-based DRP	Incentive-Based DRP	Novelty
21	Grid-Connected	To minimize operating cost	✓	✓	–
22	Grid-Connected	To minimize operating cost & emissions	✗	✗	–
23	Independent	To minimize operating cost	✓	✗	–
Proposed Method	Independent	To minimize operating cost	✓	✓	A combination of Price and Incentive DRP

Table 3 compares the current state of affairs with the planned future state of affairs. Operating costs of 36,512 cents and a peak load decrease of 10 KW were the outcomes of the same microgrid being researched in Ref. [23], with the only implementation of TOU DRP. This study introduces a new combination of DRPs for microgrid operation, together with RTP, CPP, and DLC.

3.3 Real-Time Pricing (RTP) DRP

Figure 2 displays the real-time power pricing for energy trading. With zero kilowatt-hour load shedding, the total operating cost is 35,333 cents. Just like in the earlier example, a DR program may be implemented at no expense. The power output from various producing sources is shown in Figure 3(c) for this situation.

With the RTP program in place, demand is reduced during both off-peak and peak times, moving it to low-load periods. Demand drops 14.62 kWh during peak hours and rises 7.6 kWh during low-load hours as a result of self-elasticity. The demand is reduced by 63.06 kWh and 17.73 kWh is moved to low-load hours as a result of cross-elasticity. Here, the maximum demand decrease of 12.71 kWh exceeds that of TOU-DRP. Contributing to the extension of the battery life, the discharge rate is 73.81 kWh lower compared to the TOU-DRP scenario.

3.4 Critical Peak Pricing (CPP) DRP

Due to an unforeseen surge in demand, this DRP is implemented. Prices are quite high (60 cents/kWh) from 9 to 11, but otherwise, TOU rates are in effect. With no load shedding and an operational cost of 34,896 cents, the peak decrease in this example is 14.93 kWh. Using DRP in this application won't cost you a dime. The power output from various producing sources in this situation is shown in Figure 3(d).

3.5 Direct Load Control (DLC) DRP

Participating consumers can earn incentive payments or reduced power bills when the utility or microgrid operator reduces a portion of their load in the event of a system contingency. Customers are not penalized if they choose not to participate in this program as it is entirely optional.

In exchange for reducing power use during peak hours, the microgrid operator agrees to pay customers 20 cents per kilowatt-hour. With the incentive offered, consumers are motivated to reduce peak consumption. The implementation of DRP with 0% load shedding adds 692 cents to the overall cost of this scheme, which comes to 37,292 cents. Customers save 830.36 cents because of the bonus. Various producing sources' power outputs are displayed in Figure 3(e). As a result of incentives, the demand is reduced by 34.63 kWh due to both self- and cross-elasticity, with 23.62 kWh being shifted to low and off-peak hours due to cross-elasticity alone. A total of 77.85 kWh is discharged from the battery. This case's peak demand drop of 4.8 KW is less severe than that of earlier instances

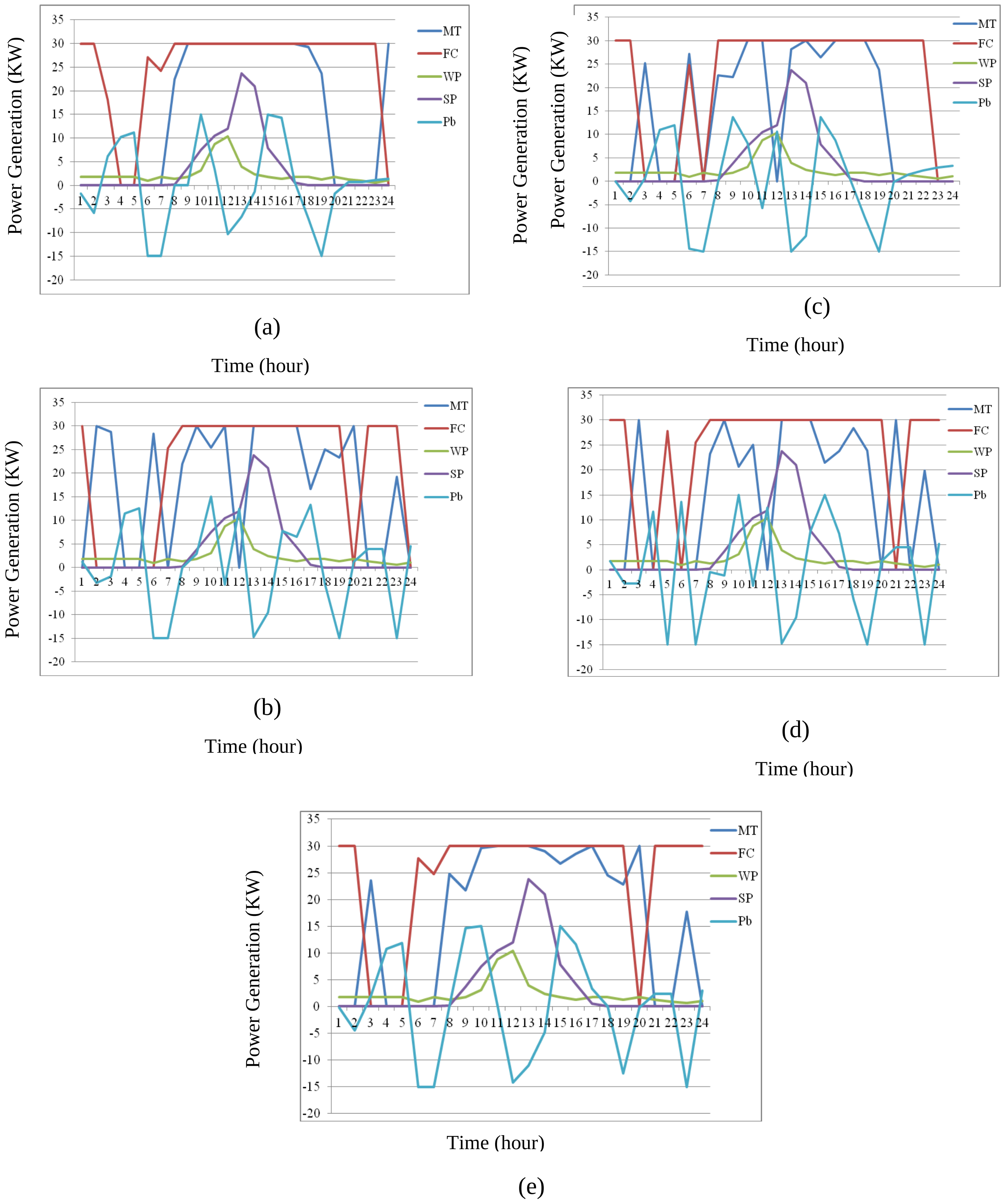

Figure 3. Power output of generating sources with (a) No DRP (b) TOU-DRP (c) RTP-DRP (d) CPP-DRP and (e) DLC DRP

Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 31 No. 1 (2024)

Table 4. Simulation Results for 20% Consumers' Participation under Various DRPs

	Without DRP	Various DRPs			
		TOU	RTP	CPP	DLC
Operating Cost(cents)	43,517	35,931	35,333	34,896	37,293
Load Shedding (kWh)	17.68	0	0	0	0
Consumers' Profit (cents)	0	-922.2	-864.94	-1351.06	830.36

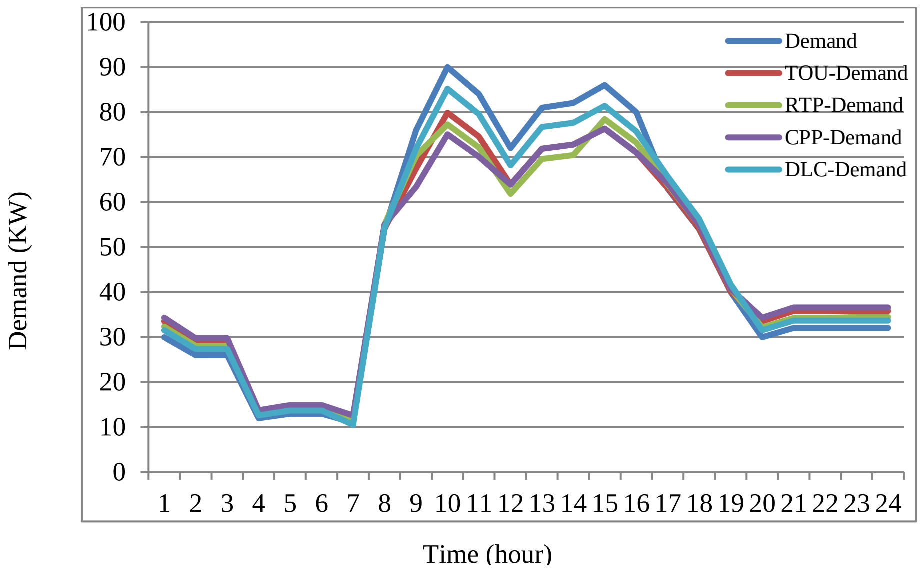

Figure 4. Modified demand after implementing different DRPs

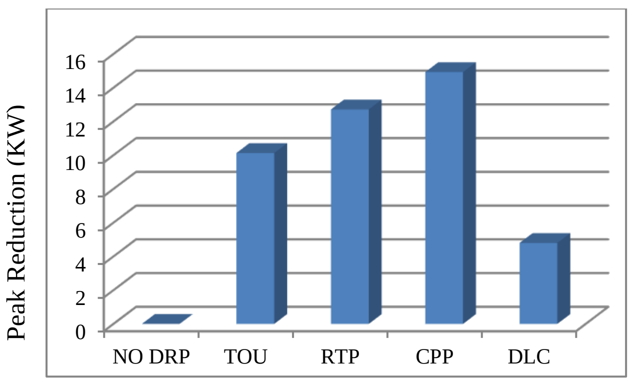

Figure 5. Peak reduction in different DRPs

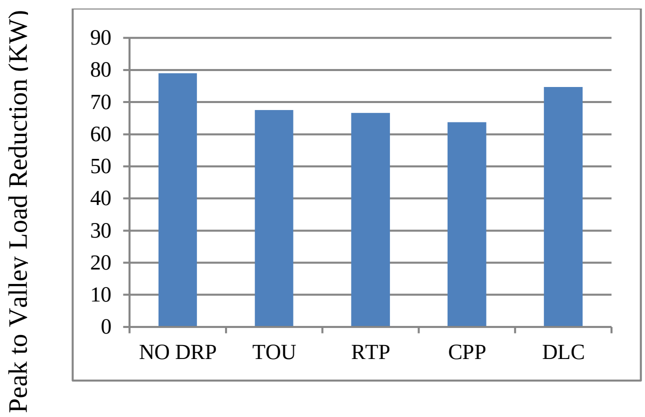

Figure 6. Peak-to-valley load reduction using DRPs

Optimization results with and without DRPs are tabulated in Table 4. Operating costs are clearly reduced with the deployment of DRPs in all scenarios, with CPP-DRP showing the greatest decrease. In all DRPs, the operator of the microgrid reduces load shedding to zero. with all DRPs, the consumer's profit is negative, meaning they lose money. The worst-case scenario is CPP-DRP, however with DLC-DRP, they actually make money.

Figure 4 shows how the demand curve changed when RTP, TOU, CPP, and DLC DRP were implemented. It is clear that demand drops across the board in all DRPs during peak hours (9–16) and then shifts to low-load times. Figures 5 and 6 show two important aspects of microgrid operation: the minimum peak-to-valley gap and the largest peak-to-valley decrease, which are achieved in CPP-DRP and RTP DRP, respectively.

3.6 Implementing a Novel RTP+DLC DRP

Similar to RTP-DRP, this initiative gives customers access to real-time electricity rates and offers a 20 cents/kWh reward for reducing their energy usage. At low-load hours, the FC and renewable generation provide most of the load, whereas MT units are typically turned off due to higher bids. At the same time, the battery is charging. Turning on the MT unit causes the battery to drain as the load grows. A total of 82.03 kWh of electricity is discharged by the battery.

A total of 36,584 cents will be spent on operations, with 1,711 cents going toward DRP implementation. Here, the microgrid operator doesn't have to worry about load shedding, and consumers may enjoy a profit of 662.49 cents. Figure 7 displays the power production from various producing sources; hence, this software delivers the benefit of both Price and Incentive-based DRP. The program's impact on demand is seen in Figure 8, which shows a peak reduction of 12.81 KW. With a load factor of 59.28%, this DRP now outperforms all but RTP and DLC DRPs.

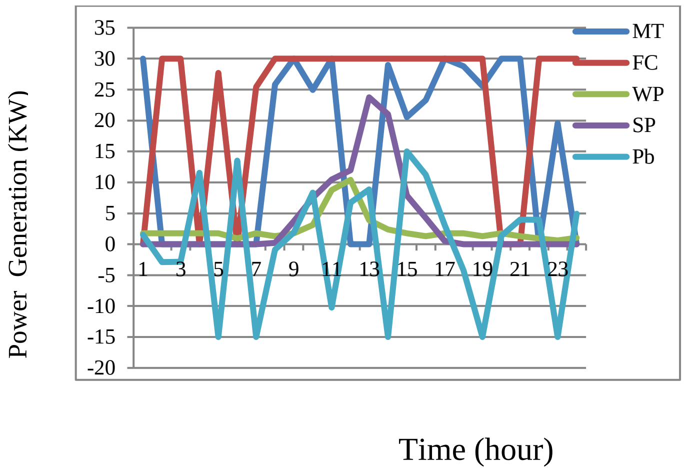

Figure 7. Power Output of Different Generating Units after Implementing RTP+DLC DRP

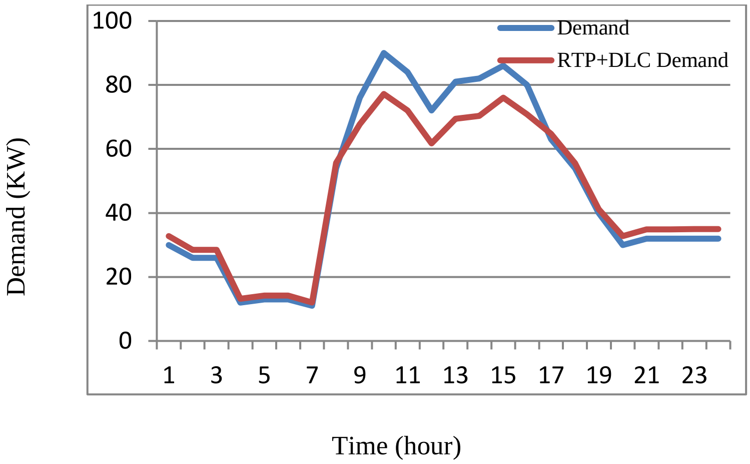

Figure 8. Change in Demand after Implementing RTP+DLC DRP

Table 5. Simulation Results for 20% Consumers' Participation after Implementing RTP+DLC DRP

	Operating Cost (cents)	Load Shedding (kWh)	Customers' Profit (cents)
RTP+DLC DRP	36,584	0	662.49

As illustrated in Table 5, combining DRPs, significantly reduces operating costs and load shedding and boosts consumer benefits compared to implementing only one type of DRP.

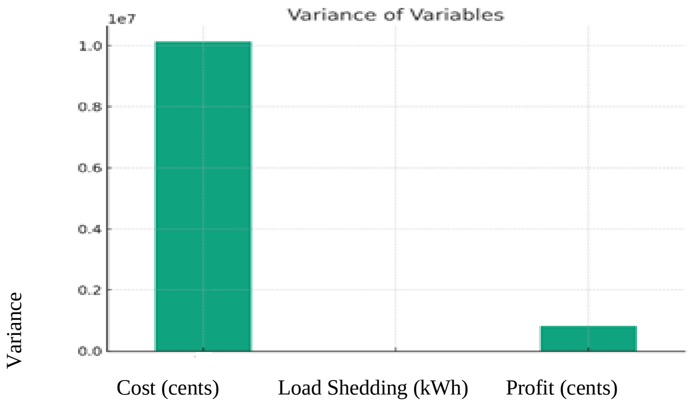

Figure 9: Variance of Variables

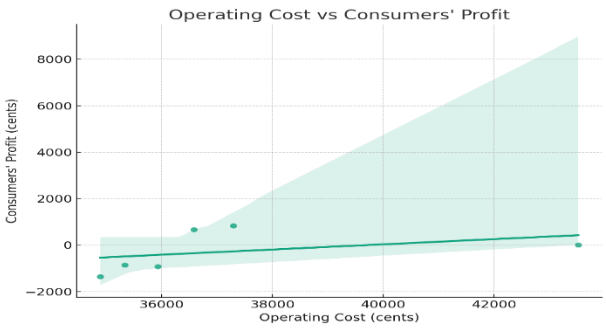

Figure 10: Operating Cost Vs Consumer’s Profit

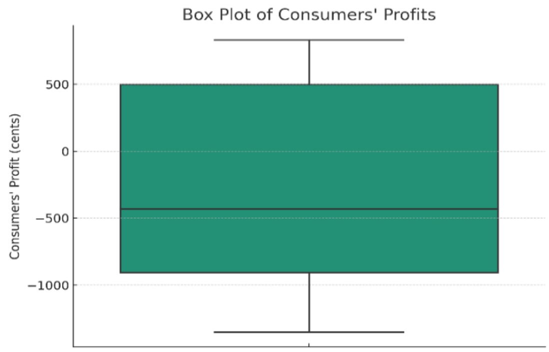

Figure 11: Box Plot of Consumers’ Profits

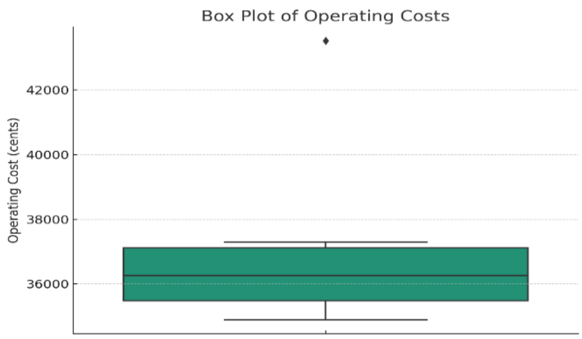

Figure 12: Box Plot of Operating Costs

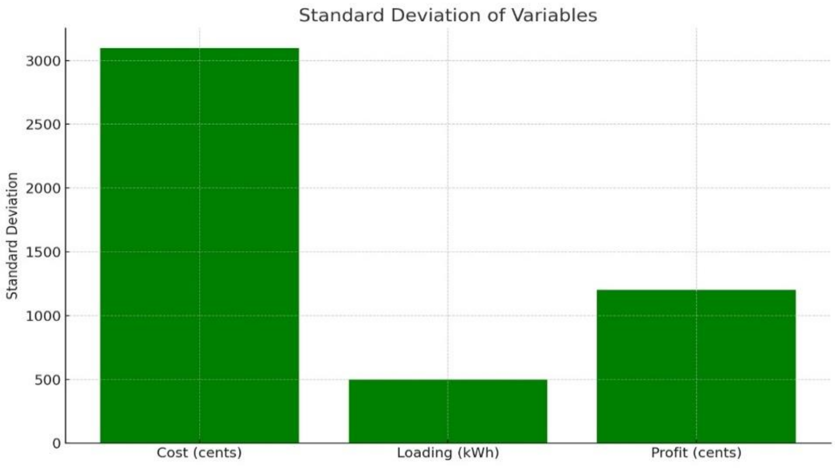

Figure 13: Standard Deviation of Varaibles

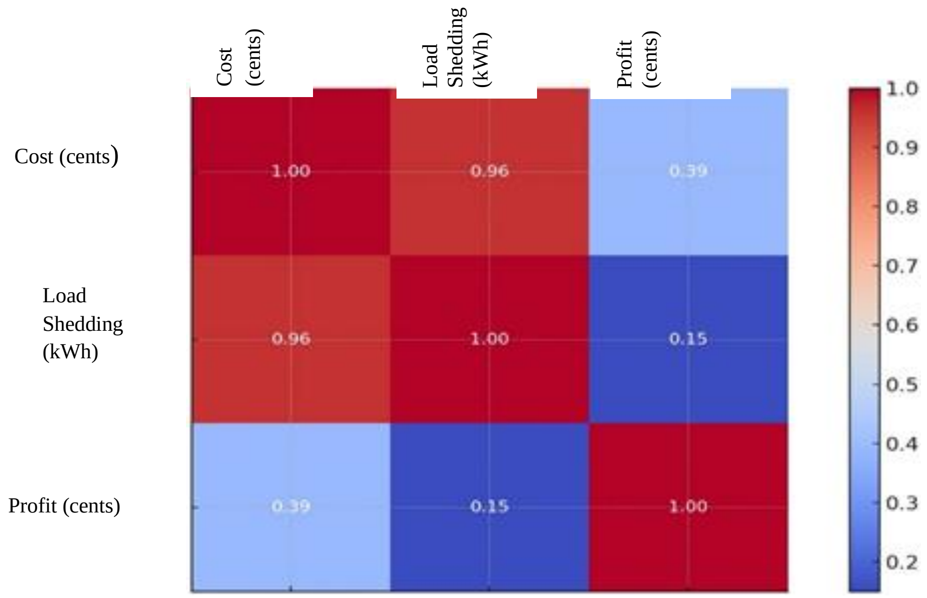

Figure 14: Correlation Matrix

CONCLUSION

A variety of Demand Response Programs (DRPs) based on prices and incentives were implemented to optimize power production scheduling in an Independent Microgrid. To enhance the efficiency of the entire 24-hour operational expenses, a new combination of these DRPs was implemented using GAMS software. Without the deployment of DRPs, consumers would have seen no noticeable benefits, and operational costs would have been 429.87 €ct and 17.18 kWh, respectively. By incorporating Time-of-Use (TOU), Real-Time Pricing (RTP), Critical Peak Pricing (CPP), and Demand Limiting Control (DLC) DRPs with 20% customer engagement, we achieved significant savings in operating costs—17.43%, 18.8%, 19.81%, and 14.3%, respectively—while eliminating load shedding. The main goal of DRP, peak reduction, was accomplished in these programs, with values of 10.13 KW, 12.71 KW, 14.93 KW, and 4.8 KW, respectively. Operating cost reduction from the base scenario was greatest for CPP DRP and lowest for DLC DRP due to related expenditures. Importantly, DLC-DRP solely benefited customers; everyone else incurred costs for demand shifting and lost out. Customers were most negatively impacted by CPP and TOU, making RTP the preferable option.

The focus of this study is on the results of the simulations of the new combined RTP+DLC-DRP, which reduced operating costs by 15.93% with no load shedding. A 12.81 KW drop in peak demand was accompanied by a significant 662.49% rise in consumer profits. A longer battery life resulted from the reduced battery discharge power due to the use of different DRPs. Thus, both the Microgrid operator and its customers would benefit from the suggested merger. Furthermore, operational expenses were significantly reduced due to an increase in the number of active consumer participations in DRPs. Crucially, Microgrids connected to the grid can benefit from the proposed initiative.

Future work will focus on developing a multi-objective stochastic model specifically for grid-connected Microgrids, with the ultimate aim of promoting environmental cleanliness. This expansion aims to further reduce operational expenses and carbon emissions by investigating new permutations of DRPs, thereby improving sustainability.

REFERENCES

[1] H. Kuang, S. Li, Z. Wu., “Discussion on Advantages and Disadvantages of Distributed Generation Connected to the Grid,” *2011 International Conference on Electrical and Control Engineering*, pp. 170-173, 2011.

[2] V. K. Garg, S. Sharma, “Overview on Microgrid System,” *in IEEE 5th International Conference on Parallel, Distributed and Grid Computing (PDGC)*, Solan, India, Dec. 2018.

[3] G. Shahgholian, “A brief review on microgrids: Operation, applications, modeling, and control,” *International Transactions on Electrical Energy Systems*, vol. 31, no. 6, e12885, 2021.

[4] X. Zhou, T. Guo and Y. Ma, “An Overview on Microgrid Technology,” *Proc. of IEEE 5th International Conference on Mechatronics and Automation (ICMA)*, pp. 76-81, 2015.

[5] H. J. Lee, B. H. Vu, R. Zafar, S. W. Hwang and I.Y. Chung, “*Design Framework of a Stand-Alone Microgrid Considering Power System Performance and Economic Efficiency*,” *Energies*, vol.14, no. 2, p. 457., 2021.

[6] R. Siddaiah, R.P. Saini. “A Review on Planning, Configurations, Modeling and Optimization Techniques of Hybrid Renewable Energy Systems for Off-Grid Applications,” *Renewable and Sustainable Energy Reviews*, vol. 58, pp. 376–396, 2016.

[7] X. Tan, Q. Li, H. Wang, “Advances and Trends of Energy Storage Technology in Microgrid,” *International Journal Electrical Power Energy System*, vol. 44, no. 1, pp. 179-91, 2013.

[8] M. P. Moghaddam, A. Abdollahi, M. Rashidinejad, “Flexible Demand Response Programs Modeling in Competitive Electricity Markets,” *Applied Energy*, vol. 88, no. 9, pp. 3257–3269, 2011.

[9] M. Rahmani-Vanderbilt, “Modeling Nonlinear Incentive-Based and Price-Based Demand Response Programs and Implementing on Real Power Markets,” *Electrical Power System Research*, vol. 132, pp. 115–124, 2016.

[10] H. Du, S. Liu, Q. Kong, W. Zhao and D. Zhao, “A Microgrid Energy Management System with Demand Response”, 2014 China *International Conference on Electricity Distribution. CICED 2014*, pp. 551-554, 2014.

[11] H. A. Aalami, M.P. Moghaddam and G. R. Yousefi, “Demand Response Modeling Considering Interruptible/Curtailable Loads and Capacity Market Programs,” *Applied Energy*, vol. 87, no. 1, pp. 243–250, 2010.

[12] C. Deckmyn, J. V. Vyver, T. L. Vandoorn, B. Meersman, J. Desmet, and L. Vandevelde, “Day-Ahead Unit Commitment Model for Microgrids,” *IET Generation, Transmission & Distribution*, vol. 11, no. 1, pp. 1-9, 2017.

[13] E. Dehnavi, H. Abdi, “Optimal Pricing in Time of Use Demand Response by Integrating with Dynamic Economic Dispatch Problem,” *Energy*, vol. 109, pp. 1086–1094, 2016.

[14] H. Aalami, G.R. Yousefi, M. P. Moghadam, “Demand Response Model Considering EDRP and TOU Programs,” *IEEE/PES Transmission and Distribution Conference and Exposition*, pp. 21-24, 2008.

[15] A. Asadinejad, K. Tomsovic, “Optimal Use of Incentive and Price Based Demand Response to Reduce Costs and Price Volatility,” *Electric Power System Research*, vol. 144, pp. 215–223, 2017.

[16] J. Wang, C. Kang, “Distributed Real-Time Demand Response Based on Lagrangian Multiplier Optimal Selection Approach,” *Applied Energy*, vol. 190, pp. 949–959, 2017.

[17] J. Aghaei, M.I. Alizadeh, P. Siano, and A. Heidari, “Contribution of Emergency Demand Response Programs in Power System Reliability,” *Energy*, vol. 103, pp. 688-696, 2016.

[18] A. Ajoulabadi, S. N. Ravadanegh, B. M. Ivatloo, “Flexible Scheduling of Reconfigurable Microgrid-Based Distribution Networks Considering Demand Response Program,” *Energy*, vol. 196 (117024), 2020.

[19] T. Khalili, A. Jafari, M. Abapour, B. M. Ivatloo, “Optimal Battery Technology Selection and Incentive-Based Demand Response Program Utilization for Reliability Improvement of an Insular Microgrid,” *Energy*, vol. 169, pp. 92-104, 2019.

[20] E. Shahryari, H. Shayeghi, B. M. ivatloo, M. Moradzadeh, “An Improved Incentive-Based Demand Response Program in Day-Ahead and Intra-Day Electricity Market,” *Energy*, vol. 155, pp. 205-214, 2018.

[21] M. H. Imani, M. J. Ghadi, S. Ghavidel, L. Li., “Demand Response Modeling in Microgrid Operation: A Review and Application for Incentive-Based and Time-Based Programs,” *Renewable and Sustainable Energy Review*, vol. 94, pp. 486–499, 2018.

[22] A. Moghaddam, A. Seifi., T. Niknam, “Multi-Operation Management of a Typical Micro-Grids Using Particle Swarm Optimization: A Comparative Study,” *Renewable and Sustainable Energy Reviews*, vol. 16, no. 2, pp. 1268– 1281, 2012.

[23] M. H. Imani, P. Niknejad, M.R. Barzegaran, “Implementing Time-Of-Use Demand Response Program in Microgrid Considering Energy Storage Unit Participation and Different Capacities of Installed Wind Power,” *Electrical Power System Research*, vol. 175 (105916), 2019.

[24] A. Maherbani, H. Mardani, M. S. Ghazizadeh, “Optimization of Isolated Microgrid in the Presence of Renewable Energy Sources and Demand Response Programs,” *IEEE 11th Smart Grid Conference*, pp. 1-5, 2021.

[25] S. Kakran, S. Chanana., “Operation Management of a Renewable Microgrid Supplying to A Residential Community Under the Effect of Incentive-Based Demand Response Program,” *International Journal of Energy and Environmental Engineering*, vol. 10, pp. 121-135, 2019.

[26] S. R. Salkuti, "Optimal Operation of Microgrid Considering Renewable Energy Sources, Electric Vehicles and Demand Response," *E3S Web of Conferences,* vol. 87 (01007), 2019.

[27] L. Barrios, A., Nozal, J., Valreno, I., Vera, J. Martinez-Ramos, "Stochastic Unit Commitment in Microgrids: Influence of the Load Forecasting Error and the Availability of Energy Storage," *Renewable Energy,* vol. 146, pp. 2060-2069, 2020.

[28] N. D. Tuyen, Linh, H.T., T.X. Hung, D.V. Long. "A Mixed-Integer Programming Approach for Unit Commitment in Microgrid with Incentive-Based Demand Response and Battery Energy Storage System," *Energies,* vol. 15, 7192, 2022.

[29] J. Wang, K. J. Li, Y., Liang, Z., Javid, "Optimization of Multi-Energy Microgrid Operation in the Presence of Heterogenous Energy Storage, and Demand Response," *Applied Science,* vol. 11, 1005, 2021.

[30] M. Nemati, M. Braun, S. Tenbohlen, "Optimization of Unit Commitment and Economic Dispatch in Microgrids Based on Genetic Algorithm and Mixed Integer Linear Programming," *Applied Energy,* vol. 210, pp. 944-963, 2018.

[31] T. R. Olorunfemi, and N. L. Nwulu, "Multi-Agent-Based Optimal Operation of Hybrid Energy Sources with Demand Response Programs," *Sustainability*, vol. 13, no. 14, 7756, 2021.

[32] Y. Li, K., Li, Z., Yang, Y., Yu, R., Xu, M. Yang, "Stochastic Optimal Scheduling of Demand Response- Enabled Microgrid with Renewable Generations: An Analytic Heuristic Approach," *Journal of Cleaner Production*, vol. 330, 129840, 2022.

[33] M. Sedighizadeha, M. Esmailib, A. Jamshidia and M. H. Ghaderia, "Stochastic Multi-Objective Economic Environmental Energy and Reserve Scheduling of Microgrids Considering Battery Energy Storage System," *Electrical Power and Energy Systems,* vol. 106, pp. 1-16, 2019.

[34] V.V.S.N. Murty, and A. Kumar, "Multi-Objective Energy Management in Microgrids with Hybrid Energy Sources and Battery Energy Storage Systems," *Prot. And Cont. of Modern Power System*, vol. 5, no. 2, pp. 1-20. 2020.

[35] B. Day, S. Mishra, F.P. Marquez, "Microgrid System Energy Management with Demand Response Program for Clean and Economical Operation," *Applied Energy*, vol. 334 (120717), 2023.

[36] I. Rendroyoko, N.I. Sinisuka, V. Debusschere, and D. Koesrindartoto "Integration Method of Unit Commitment Using PL-GA Binary Dispatch Algorithm for Intermittent RES in Isolated Microgrids System," *International Journal on Electrical Engineering and Informatics*, vol. 13, no. 2, pp. 449-464. 2021.

[37] M. Ali, M.A. Abdulgalil, I. Hahiballah, and M. Khalid, "Optimal Scheduling of Isolated Microgrids with Hybrid Renewables and Energy Storage Systems Considering Demand Response," *IEEE Access* 11: 80266-80273, 2023.

[38] R. Swami, S.K. Gupta, "Optimal Operation of Microgrid with Reduced Emission by Using Demand Response Program," *International Journal of Contemporary Architecture*, vol. 8(2), 2021.

[39] S. L. L. Wynn, B. Marungsri, T. Boonraksa and P. Boonraksa, "Decentralized Energy Management System in Microgrid Considering Uncertainty and Demand Response," *Electronics,* vol 12, pp. 237, 2023.

[40] R. Swami, S.K. Gupta, "Optimization of Standalone Microgrid's Operation Considering Battery Degradation Cost," *Proceedings of International Conference on Computational Intelligence and Emerging Power System. Algorithms for Intelligent Systems. Springer, Singapore*, pp. 267-277, 2022.

[41] Gali, A Sharma, SK Gupta, M Gupta, MVG Varaprasad, "Grid Synchronization of Photovoltaic System with Harmonics Mitigation Techniques for Power Quality Improvement Deregulated Electricity Structures and Smart Grids, 149-162, 2022.

[42] CS Kudarihal, S Kumar, M Gupta, "Econometrics and Time Series Analysis of a Grid-Connected Rooftop Solar System and Prosumers Experience in a Smart Grids Scenario: A Case Study" 2023 Fifth International Conference on Electrical, Computer and Communication Technologies (ICECCT), pp. 1-6, 2023, (IEEE).