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Muhammad Shahzad Pansota
MNS-UET Multan: Muhammad Nawaz Sharif University of Engineering and Technology
Haseeb Javed
MNS-UET Multan: Muhammad Nawaz Sharif University of Engineering and Technology
Abdul Muqeet (abdul.muqeet@uettaxila.edu.pk)
Punjab Tianjin University of Technology Lahore https://orcid.org/0000-0002-0866-4165
Muhammad Irfan
Beijing Institute of Technology
Moazzam Shehzad
University of Engineering and Technology
Rehan Liaqat
University of Engineering and Technology

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Scheduling and Sizing of Campus Microgrid Considering Demand Response and Economic Analysis

Muhammad Shahzad Pansota[1], Haseeb Javed[1], Hafiz Abdul Muqeet[2], M Irfan[3], Moazzam shehzad[4], Rehan Liaqat[5]

[1]Department of Electrical Engineering, Muhammad Nawaz Sharif University of Engineering and Technology, Multan 60000, Pakistan.
[2]Department of Electrical Engineering Technology, Punjab Tianjin University of Technology Lahore, Punjab, 54770, Pakistan.
[3]School of Management and Economics, Beijing Institute of Technology, Beijing 100081, China.
[4]Department of Electrical Engineering, University of Engineering and Technology (RCET), Lahore, Punjab, 54890, Pakistan.
[5]Department of Electrical Engineering, University of Engineering and Technology, Taxila, Punjab, 54890, Pakistan.
[5]Department of Electrical Engineering, Government College University Faisalabad, Faisalabad 38000, Pakistan

Corresponding author: Hafiz Abdul Muqeet (e-mail: abdul.muqeet@uettaxila.edu.pk).

ABSTRACT

Background: Current energy systems face multiple problems related to inflation in the energy prices, reduction of fossil fuels, and greenhouse gas emissions in disturbing the comfort zone of energy consumers and affordability of power for large commercial customers. This kind of problem can be alleviated with the help of optimal planning of Demand Response policies and with distributed generators in the distribution system. The objective of this article is to give a strategic proposition of an energy management system for a campus microgrid (µG) to minimize the operating costs and to increase the self-consuming energy of green DGs. To this end, a real-time-based campus is considered that is currently providing its loads from the utility grid only. Yet, according to the proposed given scenario, it contains the solar panels and wind turbine as a non-dispatchable DG while a diesel generator is considered as a dispatchable DG. It also incorporates the energy storage system with the optimal sizing of BESS to tackle with multiple disturbances that arise from solar radiations.
Results: The resultant problem of linear mathematics has been simulated and plotted in MATLAB with mixed-integer linear programming. Simulation results show that the proposed given model of EMS minimizes the grid electricity costs by 31% in case of summer and 38% in case of winter respectively, while the reduction of GHG emissions per day is 780.68 and 730.46 kg for the corresponding summer and winter seasons. The general effect of a medium-sized solar PV installation on carbon emissions and energy consumption costs is also observed.
Conclusion: The substantial environmental and economic benefits compared to the present case prompt campus owners to put investment in the DGs and to install large-scale energy storage.

Keywords: Smart grid, batteries, campus microgrid, renewable energy resources, prosumer market, distributed generation, energy management system, and energy storage system.

ACRONYM AND NOMENCLATURE

A. ACRONYMS

BSOC	Battery state of charge
BESS	Battery energy storage system
DERs	Distributed energy resources
DG	Distributed generator
DSM	Demand-side management
EV	Electric Vehicle
FIT	Feed-in-Tariffs
TOU	Time of use
MILP	Mixed integer linear Programming
GHG	Greenhouse gas
LP	Linear Programming
RERs	Renewable energy resources
PV	Photovoltaic

B. CONSTANTS AND VARIABLES

$BSOC_0$	The starting value of BSOC at time 0 (%)
$BSOC_t$	BSOC value at time interval t
$BSOC_{max}$	Maximum BSOC level (%)
$BSOC_{min}$	Minimum BSOC level (%)
C_t^{dg}	Cost of Diesel generator ($)
C_t^{es}	Cost of Storage degradation ($)
C_t^{e}	Net cost of energy ($)

C_t^{WT}	Net cost of wind energy ($)
C^{ES}	Rated capacity of energy storage (kWh)
J	Overall operations cost
I	Solar irradiance
μG	Microgrid
P_t^{pv}	solar PV Output power (kW)
E_{net}^{g}	Net energy exchange with the grid
P_t^{bat}	The output power of the battery storage system (kW)
P_t^{ch}	Charging power of the battery (kW)
$P_{ch,max}^{bat}$	Maximum charging power of the battery (kW)
$P_{dch,max}^{bat}$	Maximum discharging power of the battery (kW)
P_t^{dch}	Discharging power of storage system (kW)
ΔP^{bat}	Gradient power of storage system (kW)
P_t^{dg}	The output power of diesel generator
SOHM	Minimum state of health
P_t^{g}	Grid power (kW)
P_t^{l}	Load demand of prosumer (kW)
P_{max}^{g}	Maximum power exchange limit of utility grid (kW)
P_{min}^{g}	Minimum power exchange limit of utility grid (kW)
T_G	Diesel generator rated capacity
μ	Mean of solar irradiance
$\frac{\mu_t^{ch}}{\mu_t^{dch}}$	Storage charging integers/storage discharging integers
λ_t	Electricity rate ($/kWh)
σ	Standard deviation of the solar irradiance
α	Diesel generator fuel curve intercept
η_{pv}	The efficiency of Solar panel
β_{pv}	Area of a Solar panel
β	Diesel generator fuel curve slope

I. INTRODUCTION

Power systems have been going through many problems which include greenhouse gas emission (GHG), inflating consumption cost, complex network overloading, and so on. The normal grid may not be able to solve these issues, but, the evolving microgrid system with distributed generators (DGs) equipped with the intelligent distribution system and the energy storage systems has the capacity to mitigate problems related to the scheduling of resources by implementing the demand response solutions. A campus microgrid (µG) on the other hand, consists of storage systems, onsite DGs, and organized loads [1]. It may additionally operate both in islanded mode or in grid-connected mode [2]. The developing trend of microgrids provides an effective solution to monitor the system intelligently and it has the abilities of self-recovery, persuasive control, and high-tech control with the help of overall sensors installation [3]. The smart and efficient grid offers diverse possibilities for renewable energy implementation for prosumer µGs by integrating the energy management (EMSs) systems. Various kinds of energy management systems require secure interaction among prosumer and conventional grid to operate the control devices intelligently [4]. However, the distribution network includes a group of µGs wherein every µG acts as a self-governing distribution node, consequently, µGs consist of onsite DGs, energy storage systems, and DR programs which may play a significant role in minimizing the network overloading and electricity cost [5], [6]. The aforementioned benefits are greatly reported for multiple µGs with excessive loads. University campus buildings are one of the excessive loads µGs that shortfall under the load customers due to the changing nature of electrical loads. With the presence of onsite electricity generation resources, this type of institutional buildings can distribute its surplus electricity to the grid community while serving as a general prosumer [7]. In the same way, they can also import required energy from the utility in extreme load conditions when campus onsite DGs and energy storages are inadequate to satisfy the load demand [8]. The actual contribution of such campus µG in operations of the grid not only minimizes their energy operational cost but also assists in the distribution network. Microgrid operators also give proposition on many incentives-based and price-based multiple DR programs to appeal to the large-scale customers in the energy markets [9]. Energy managing solutions are used with the existing resources in helping the best optimal dispatch to meet the load demand at a decreased price and by ensuring their active participation in supporting the grid operations [10].

This research highlights and focuses on the EMS development and improvement for a prosumer µG (campus) having onsite DGs and an energy storage facility. The given proposition of EMS can effectively manage the bidirectional power flow optimally among utility networks and µG, and optimally schedules the charging-discharging patterns of ESS accordingly to reduce the cost of energy. For general analysis, the real load of an actual campus (U.E.T, Taxila) has been taken into consideration. Currently, the considered campus µG has an electrical grid network connection from the nearby distribution company called Islamabad Electric and Supply Company (IESCO) which also includes an external backup diesel generator and a wind power as an external source. The environmental and economic effects of solar PV-based energy storage and energy production in this proposition are also investigated.

II. RELATED WORK

A microgrid model comprised of solar panels, combined heat, and power (CHP), diesel engines, and storage battery for various cities of (Pakistan) was simulated in [11] by HOMER Pro microgrid software. The main purpose was to minimize the electricity generation cost, total net cost, and yearly GHG emissions while improving the grid sales and to increase the yearly waste heat recovery methods of thermal units that transfer the additional waste heat into extra energy. The analysis had been executed in two types of modes: islanded mode and grid-connected mode. It was studied and analyzed that every type of city has an optimum special objective function, however, the competent authority makes an optimum decision to choose an optimal city according to their objective. The overall analysis shows that Lahore city has the minimum GHG emissions (1000.314 tons) annually while the city Quetta has the largest grid sales (8,322,368 kWh) annually among various cities.

On the other hand, Rehman *et al.* [12] proposed a microgrid model for the customers having a national grid, PV units, batteries, flexible loads while maintaining the grid reliability and sustainability. The feasibility of the given system was analyzed for the Levelized cost (LCOE) of energy and the net cost with the help of HOMER Pro software. The electricity cost having no grid outage was calculated (0.135$ per kWh). The results have been carried out to analyze the fluctuating effects of solar irradiance and grid outages. The best possible setup for the household microgrid was calculated to be solar PV capacity with 2 kW, battery energy storage with 1200 Ah, and power converter with 1 kW. From this kind of setup, the system maintenance, and operational costs, capital costs, and the replacement cost were to be $6522, $7610, and $2833.

In [13], the authors developed a scheduling framework for the PV-Storage-based microgrid considering battery degradation cost and battery running cost. The comparative analysis had been conducted and proposed with the current literature of the MILP model (Mixed-Integer Linear Programming). The proposed system included a solar PV plant and a battery energy storage system (BESS). The proposed model minimized the electricity cost, battery degradation cost, and the peak-demand violation penalty. Besides, it addressed the two main issues; the optimum use of batteries with the help of RTCS (Real-Time Control Schemes) and to lessen the solar irradiance forecasting error. To manage the SOC (State-of-charge), the FAM (Flexible Assignment Method) technique was implemented and its costs were minimized from 36,286,470 (KRW) to 34,354,895 (KRW).

Authors of ref. [14], given a load reduction model of a utility grid keeping in view the grid availability for the residential customers by implementing the linear programming that is simulated in MATLAB software. The affordability of PV-storage systems was addressed in this paper with the consideration of multiple hours of load shedding by online optimization methods or techniques. Multiple situations of load shedding were investigated, and the results were analyzed for 8 hours of load shedding that could save almost 1000kWh and for an average household almost 1200W. Moreover, the authors observed that a 4 hours random load shedding scenario minimizes the monthly energy consumption cost up to 16%.

Li *et al.* [2], on the other hand, presented the best possible solution for the probabilistic spinning reserve of an isolated microgrid with the help of the chance-constraint linear programming approach. The proposed solution was then transformed into a MILP approach (Mixed-Integer Linear Programming) and then it was simulated in GAMS by means of a CPLEX problem solver. The core objective of the proposition was to minimize the computational time and cost and to show the best trade-off strategy that is economical for the microgrid. The proposed solution minimized the energy cost from (396.6$ -to- 394.4$) while the computational time was minimized from (673.6s to 2s) as in comparison with the HIA (Hybrid-intelligent Algorithm).

In ref. [15], the authors presented an optimal model for a battery system with multiple benefits. In this paper, the literature is addressed for four different services: energy reserves, energy arbitrage, investment deferral, and frequency regulation. At first, every service was independently observed to get the estimation of benefits for private owners of battery systems. After that, using the day-ahead market data of CAISO 2015, multiple combinations of services were analyzed. The results revealed that the best revenue generated among the four services was the frequency regulation of (121,265$) while the lowest revenue generated by the energy arbitrage service of (18,983$) and the revenue generated by all the four services were (221,817$).

Zhang *et al.* [16] given the testbed project for the campus microgrid of Georgia Institute of Technology. The proposition of this paper was given for 400 net meters and a group of 200 commercial buildings and it was performed on the OpenDSS software. A huge amount of data for the distributed system was controlled by the latest data management system. The DR (Demand Response) based strategies were implemented that aims to improve the interaction between commercial buildings and the grid. It also studied the expansion of electricity generation planning in end as future research.

In ref. [17], the authors presented the BESS (Battery Energy Storage System) model to enhance the profit of the Distribution Company (DISCO). The Conic relaxation techniques and NA (Natural Aggregation) were incorporated for the cost reduction and bidding strategy. The distributed generation (DG) was considered to minimize the errors and the given model on the other hand minimizes the transaction risk. A two-layer operational module was implemented for day-ahead optimization and real-time monitoring. The efficiency of the model was investigated by the sensitivity analysis. Multiple case studies were tested and analyzed on the 15-Bus IEEE system by considering and not considering the battery energy storage (BESS) system. The consideration of BESS in a system reduced the electricity cost in the day-ahead market from (448.49$ ~to~ 433.63$). Though, here economic feasibility of the system was unnoticed in the proposed model.

Perkovi¢ *et al.* [18] devised a theoretical factory model in which the factory performing as a prosumer. The effective multi-objective optimization model was established to find the optimum energy exchange value based on two types of costs: investment cost and operation cost. The proposed system was solved by the linear programming method on the octave 2015 and the optimum values of the conflicting parameters were found by the Pareto-optimal front technique. The MCP (Market Clearing Price) was observed in 5 different scenarios and taken as an input. Results have shown that the given model minimized both the investment and operational cost of the factory which is acting as a prosumer.

Dahraie *et al.* [19] devised a multi-approach stochastic optimization model with the immediate benefits for the demand and supply entities keeping in view the wide-ranging security provisions of frequency. The multi-approach model was implemented in GAMS by the CPLEX problem solver and due to the engagement of each customer, the particular outcomes were originated in the energy market. The residential model of the load was analyzed with the help of price-based DR (Demand Response) programs. The proposed model reduced the cost from (835.52$ -to- 773.75$) by using the incentive-based demand response program.

In [20], the authors effectively scheduled a microgrid aiming to develop a VPP (Virtual Power Plant) with the help of an algorithm called binary backtracking search (BBSA) algorithm. The renewable energy resources were incorporated in the system by an optimum controller and IEEE 14-BUS system was used as a test system to assess and validate the proposed model. The fitness function of the given model was generally compared with the BBSA and it shown that the proposed model had much better fitness function. The results show that it reduces the power losses and operating cost while improving the reliability of the microgrid. The given proposed model improves the saving of the system from (187926.396 RM -to- 222245.9262 RM) where RM is Malaysian Ringgit. To reduce the peak load and operational cost of a grid, a day-ahead scheduling of microgrid resources was presented in [21]. The variable prices and day-ahead load variation were estimated with the help of modern artificial neural network for an optimum solution. The CPLEX problem solver was used to develop the MILP (Mixed Integer Linear Programming) model in an algebraic modeling language (AMPL). The battery storage life was improved by the reduction of life cycles of energy storage system (ESS). Multiple case studies were investigated with various ESS based scenarios and the proposed model reduced the operational cost from (89.59$ ~to~ 41.23$).

Fahad *et al.*[22] presented cost-effective microgrid with the consideration of various cases for the University AMU (Ali Garh Muslim University), India. It devised the most optimal solution for the AMU campus in which wind, PV, and grid combination system is the final solution. It is configured that by HOMER software, PV, grid, and wind is the desirable solution for the AMU campus microgrid. It calculated the NPC (Net Present Cost) 17.3$ Million/ Year and CO_2 emission for the system is 35792 kg/Year.

Yang *et al.* [23] optimally scheduled the electricity generation for multi-energy renewable sources in a hub acting as a center of all the sources. The TOU (Time of use) different pricing scheme was put in consideration which is solved by the mixed-integer linear (MILP) programming model implemented in GAMS. Such random nature of distributed generations and different types of loads with various confidence level were addressed here to minimize the operational cost and to improve the effectiveness of power utilization. The analysis deducted that it increased the operational cost of the given system and also confidence level. Both the seasons of summer and winter were investigated accordingly to obtain the operational cost. It observed the cost reduction of electricity from (1092.8$ -to- 955.8$) in summer, while it observed cost reduction from (1328.6$ -to- 1105.8$) in winter season.

Li *et al.* [24] presented a day-ahead optimal scheduling of an isolated microgrid focused on the cost reduction while keeping in view of the charging station of electric vehicle also. The given model minimized the cost and increased the annual savings. An analytic (branch and bound) algorithm and hybrid heuristic (Jaya) algorithm were applied to resolve the irregularities of the system. The multiple uncertainties of photovoltaic (PV) system, wind turbine (WT) system, and electrical loads were modelled by numerous distribution functions. However, the deducted results were made comparison with some other methods and it analyzed vital reduction in costs and approximately effects of demand response while storage life of batteries were ignored. The improvements in computational time and costs were found to be (364.7s ~to~ 37.5s) and (183.16$ ~to~ 176.43$) respectively, whereas the profit from our proposed approach were improved from (140.23$ ~to~ 147.15$) as compared with the HIA approach.

Silva et al.[25] proposed an energy management solution for the operator of a microgrid (MGO) in different time-zones. In the proposed scenario, two different time-zones are implemented which are hour-ahead time-based and day-ahead time-based. Results show that power generated divided 86.68% for distributed generators (Wind power 62.99%, PV 26.85%, and Biomass 10.15%), 12.72% for outsourcing suppliers, and 0.60% for energy storage dischargers while the power consumption was 74.03% for buildings, 17.94% Electric Vehicles (EV) charges, 6.52% energy market sellers and 1.51% for electric network losses.

Raj and Kowli [26] presented an optimal scheduling formulation for the prosumer keeping in view the forecasted errors. The scheduling formulation was simulated by the stochastic MILP model to resolve various kinds of scenarios. The resource scheduling and forecasting scheduling were given here for the controllable and not controllable loads. So, two-stage multi approach stochastic control problem was presented for the prosumer by the battery energy storage to recompense the uncertainties.

In [27], the authors given an optimal design for the prosumer based energy management (EMS) system. Various protocols were considered to address the applications of energy and market scenarios. The proposed design implemented the OASIS protocols to perform various services such as communication protocols, the practical architecture, and the interaction between the prosumers.

Hoe and Coe [28] proposed a BESS scheduling model that solve the issues of demand response. The given model minimized the uncertainties in the demand response deployment and the operational system cost. The total costs were minimized from 85.1$ -to- 42.7$ with DR involvement. Energy storage technology has helped among various applications in managing different kind of microgrids. Among many applications, off-grid system applications [29], energy arbitrage [30], distribution system deferral [31], [32], [33], frequency regulation [34], demand-side management [35], peak reductions [36], and power system reliability [37] etc. are the key contributions in the energy storage system. Several technologies of ESS such as flywheel, compressed air, BESS, ultracapacitors, etc. are generally available [38]

TABLE 1. Multiple summary comparison of various approaches.

References	Power balance	DR	Grid-Connected (Bi-directional Supply)	Generation			ESS	Optimal Scheduling of ESS	Economics Analysis*	Sizing	GHG Emissions
				PV	Wind	DiG					
[39]	✓	✓	✓	×	✓	×	×	×	✓	×	×
[40]	✓	✓	✓	×	✓	✓	✓	✓	✓	×	×
[41]	×	✓	✓	✓	✓	✓	✓	✓	✓	×	✓
[42]	×	✓	✓	✓	×	✓	✓	✓	✓	✓	✓
[43]	✓	✓	×	✓	✓	✓	✓	✓	×	×	×
[44]	×	✓	✓	✓	✓	×	×	×	✓	×	×
[45]	✓	✓	✓	✓	✓	✓	✓	✓	✓	×	×
[46]	✓	×	×	×	✓	✓	✓	✓	×	×	×
[47]	✓	✓	×	✓	✓	✓	✓	✓	✓	✓	✓
[48]	×	✓	✓	✓	✓	✓	✓	✓	✓	×	✓
[49]	×	✓	×	×	✓	×	✓	×	×	✓	✓
[50]	×	✓	✓	×	✓	×	✓	✓	×	✓	✓
[51]	×	✓	×	✓	✓	×	✓	✓	×	×	×
[52]	✓	✓	✓	✓	✓	×	×	×	×	×	×
[53]	✓	✓	×	×	✓	✓	✓	×	×	×	×
[54]	✓	✓	✓	×	✓	✓	×	×	×	×	×
[55]	×	×	✓	✓	✓	✓	✓	✓	×	×	×
Proposed Model	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

*Economic analysis is expected to be done on the basis of maintenance cost, operational costs, and installation costs. Net present cost, levelized cost of energy (LCOE), and payback period, etc. are described in the respective mathematical model.

The optimum charging/discharging patterns of the energy storage system can additionally improve the efficacy and life of the battery. From all these advantages, BESS technologies are considered here in this paper among with Li-ion technology.

Several related works cited above, especially on the power management structure of the microgrid, has considered optimal planning, ESS and PV. Different researchers here studied the integration of ESS into a microgrid while examining the feasibility of solar PV, but some other researchers only focus on reducing the cost of PV and scheduling for ESS. LCOE with simultaneous consideration of energy exchange with utility, PV uncertainties, battery degradation costs, and demand response, and, as presented in

Table 1. This work investigates previously mentioned research areas and gives a concise comprehensive model of the energy management structure of a campus microgrid with the help of optimal planning for certain energy storage systems.

The main contributions of this paper are as follows.

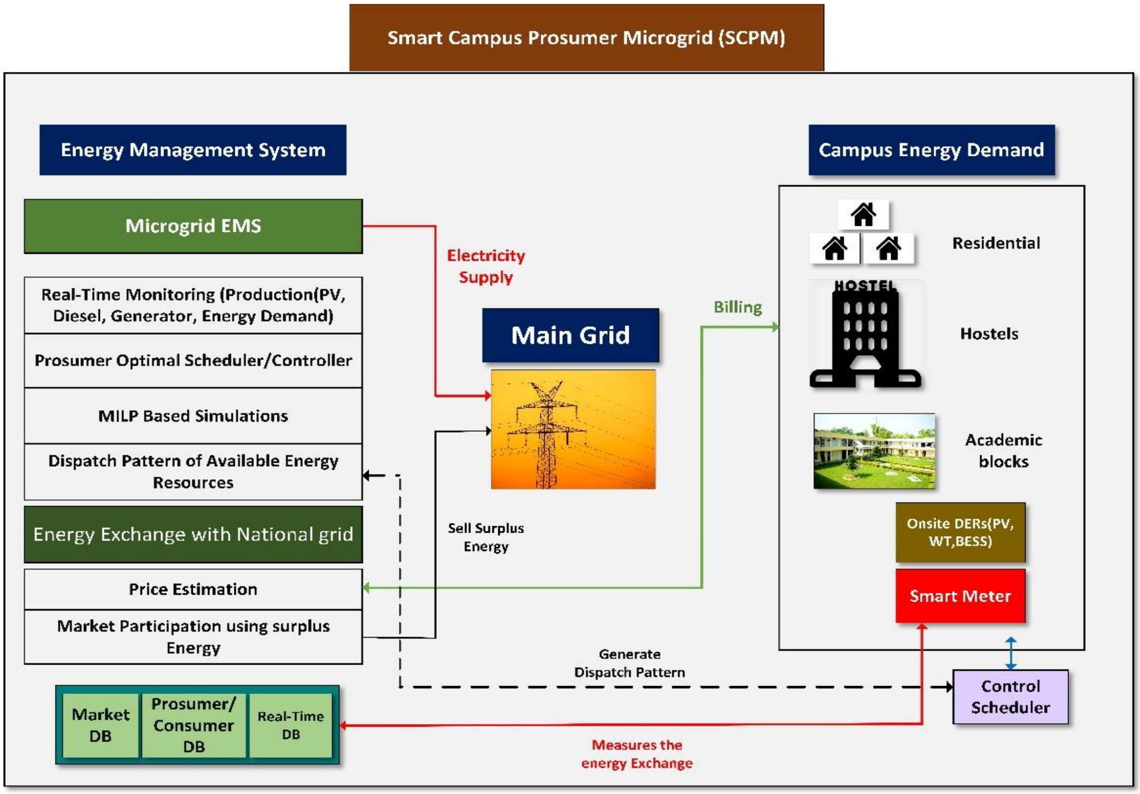

FIGURE 1. Proposed Conceptual model of EMS.

- A smart EMS is suggested for the optimal scheduling of onsite DGs, ESS, and grid power utilizing MILP with the consideration of the TOU-based demand response to enhance self-consumption and to lessen the operating costs of electricity and system load in the peak hours.
- Battery degrading cost and stochastic PV generation are employed to enhance the mathematical modeling of campus μG.
- Techno-economic effects of different sizes with environment friendly DGs and optimal scheduled ESS are investigated based in a TOU-based net metering environment.

The following sections constitute of the remainder of the paper. In Section III, the suggested system's architecture and formulation are given. The suggested model's results and discussion are presented in Section IV, and the conclusions of this article are completed in Section V.

III. PROPOSED FRAMEWORK OF THE METHODOLOGY

A. Proposed Conceptual Framework

The proposed formulation of the system that is represented in the Figure 1 consists of prosumer μG, electric grid, and EMS. The campus μG contains several kinds of energy storage technologies, loads and three different distributed energy resources (diesel generators, solar PV and wind turbine). The energy prosumer has signed a contract with the utility company through a net metering connection to trade its extra power to the utility. The given proposition of EMS employed in the prosumer network that normally takes the data of weather, load demand, unit prices, the ESS early status and the input data is taken as their associated parameters, and it search a best possible optimum solution that can satisfy the demand with the resources available without violation of its operation and designed limitations. The best result is then directed to the system control scheduler to schedule the available resources of the system. It also provides a facility to store many significant parameters also, which can be used to bring many benefits for the future purposes. Real-time market database and a prosumer database stores the electricity exchange data, prosumer load data, and price data. Though, the proposed model will be presented in the next section.

B. Problem Methodology

Keeping in view of the service life of the BESS system, the proposed mathematical model is modeled as a linear constraint optimization problem that able to lessen the operating costs of μG prosumers. The system constraints associated with some given model components that are generally mentioned below.

C. Objective Function

This proposed model has an objective to decrease the operational cost (J) of a µG, that includes the cost of energy exchange, the cost of wind turbine, diesel generators cost, and degradation cost of energy storages (2-5). Equation (1) gives the sum of different types of costs. The battery life depends on several factors, which consist of the used number of cycles, capital costs, and the overall system capacity, as shown in the equations (4-6) whereas storage is represented by η_{ch}, η_{dch}, P_t^{ch} and P_t^{ch} are respectively represented by formula (5):

$$C_T = J = \min\sum_{t=1}^{24}(\mathrm{cost}_t^E + \mathrm{cost}_t^{DG} + \mathrm{cost}_t^{ESS} + \mathrm{cost}_t^{WT} + \mathrm{cost}_t^{BESS}) \qquad (1)$$

where $cost_t^E$, $cost_t^{WT}$, $cost_t^{ESS}$, $cost_t^{DG}$ are exchange cost of energy, wind turbine cost, degradation cost of battery, and diesel generator cost at the time interval t. The campus has reserved the general time of use (TOU) tariff connection from the electricity supply company named IESCO. Throughout any interval t, the energy trade with utility grid and the energy unit price are represented by $P_{(t)}^G$ and γ_t respectively. $cost_t^{DG}$ is found out by using the rated capacity of diesel generator (T_G= 600kW), fuel intercept curve (α = 0.0166 l/h per kW), fuel curve slope (β= 0.277 l/h per kW) and the overall generated power ($P_{(t)}^{DG}$) from DG [56] as indicated in the Figure 2. The regular charging efficiency, charging power, discharging efficiency, and energy storage discharging power is characterized by $\eta_{(ch)}$, $p_{(t)}^{ch}$, $\eta_{(dch)}$, and $p_{(t)}^{dch}$ respectively and the battery net power ($P_{(battery)}$) is signified in equation (7).

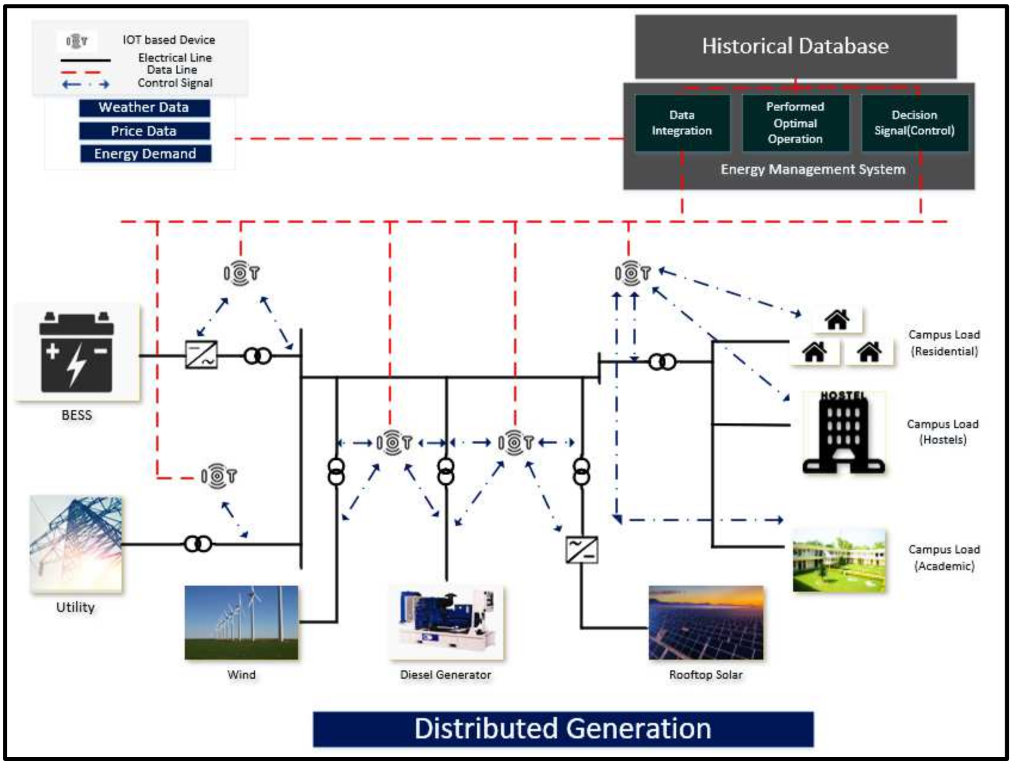

FIGURE 2. Proposed architecture of the system.

whereas,

$$cost_t^E = P_{(t)}^G \gamma_t \qquad (2)$$

$$cost_t^{DG} = \alpha T_{Gen} + \beta p_{(t)}^{DG} \qquad (3)$$

$$cost_t^{WT} = S_c . P_{rated} (\$) \qquad (4)$$

$$cost_t^{ESS} = \left(\frac{C_{cost}}{n \times CT \times 2}\right) \times \left(\eta_c p_{(t)}^{ch} + \frac{p_{(t)}^{dch}}{\eta_{dch}}\right) \qquad (5)$$

$$cost_t^{BESS} = S_{BESS}(C_i^{ESS} + C_m^{ESS} t_{om}) \qquad (6)$$

$$P_{(battery)} = \eta_{(ch)} P^{ch}{}_{(t)} - \frac{p_{(t)}^{dch}}{\eta_{(dch)}} \qquad (7)$$

D. Load Balancing Equality Constraint

The equality constraint of the load basically represents the equilibrium constraint between supply and demand. In order to attain this equilibrium, the equation (8) must be fulfilled and satisfied. Among them, P_t^{pv} and P_t^l are respectively the output of solar photovoltaic power generation in kW and the prosumer load demand.

$$P_{(t)}^G + P_{(t)}^{PV} + P_{(t)}^{Battery} + P_{(t)}^{DG} + P_{(t)}^{WT} + P_{(t)}^{BESS} = P_{(t)}^{total} \qquad (8)$$

E. Energy Storage System Constraints

ESS is not to be ignored element in the energy management system, because it assist in the supply of electrical load in the event of a grid failure [57]. Since the ESS normally cannot be easily charged or discharged immediately, its power limit has been included in the limits (9)-(13). In any interval t " $BSOC_t$ ", the battery state of charge in the ESS depends on its earlier state $BSOC_{(t-1)}$, that is merged in equation (14). In order to get rid of ESS overload and whole discharging, the BSOC maximum and minimum limits are respectively represented by $BSOC_{max}$ and $BSOC_{min}$ in equation (15). As shown in equation (16), the battery's state of charge ($BSOC_T$) at the end of a day is equivalent to its initial battery state ($BSOC_0$) occurring at the start of the day.

$$\frac{BSOC_{t-1} - BSOC_{max}}{100} C^{es} \leq P_{(t)}^{Battery} \tag{9}$$

$$P_{(t)}^{Battery} \leq \frac{BSOC_{(t-1)} - BSOC_{(min)}}{100} C^{es} \tag{10}$$

$$0 \leq \eta_{(ch)} P_{(t)}^{ch} \leq Y_t^{ch} P_{(ch,max)}^{Battery} \tag{11}$$

$$0 \leq \frac{P_{(t)}^{dch}}{\eta_{(dch)}} \leq Y_t^{dch} P_{(dch,max)}^{Battery} \tag{12}$$

$$Y_t^{ch} + Y_t^{dch} \leq 1 \forall t \tag{13}$$

$$BSOC_{(t)} = BSOC_{(t-1)} - \frac{100 \times \eta_{(dch)} P_{(t)}^{dch}}{C^{es}} - \frac{100 \times P_{(t)}^{dch}}{C^{es} \eta_{(dch)}} \tag{14}$$

$$BSOC_{(min)} \leq BSOC_{(t)} \leq BSOC_{(max)} \tag{15}$$

$$BSOC_{(T)} = BSOC_{(0)} \tag{16}$$

The battery power output P_t^{bat} has been added to the equality constraint given in equation (8) to effectively schedule the energy participation in EMS. The positive and negative values of P_t^{bat} represents ESS charging and discharging, respectively. In any interval "t", the ESS charging and discharging are signified by the two integer variables μ_t^{ch} and μ_t^{dch}, respectively. To best avoid the BESS charging and discharging problem at the similar timings, the given binary variables available in the expressions (11) - (13) cannot be "1" at the similar times. For any of these variables, a value equal to "1" indicates the activation mode.

The output power gradient of the energy storage is given below:

$$\left| P_{(t)}^{Battery} - P_{(t+1)}^{Battery} \right| \leq \Delta P^{Battery} \tag{17}$$

F. Optimal Sizing of Bess

In order to increase the economic benefit, an optimal sizing methodology is adopted to provide a peak load shaving strategy for an electrical consumer by and enhancing the BESS lifetime.

$$P_{(t)}^{DG} = P_{fi}^{wt}(t) + P_{fi}^{PV}(t) \tag{18}$$

$$P_{(t)}^{DG} = P_{(t)}^{dl} - P_{(t)}^{DG} \tag{19}$$

$$P^D{}_{(t)} = P^{dl}{}_{(t)} - P^{DG}{}_{(t)}; \;\; P^{dl}{}_{(t)} > P^{DG}{}_{(t)} \tag{20}$$

In equation (18-20), $P_{(t)}^{DG}$ is the distributed generation power at time interval t, $P_{(t)}^{dl}$ is the power of the actual demand of the load at time interval t, and $P^D{}_{(t)}$ is the deficiency of power at the time t.

$$E^D = \sum_{t=1}^{t=24} P^D{}_{(t)} \tag{21}$$

$$S_{BESS} = \frac{E^D}{(1-\rho)} \tag{22}$$

$$Cost_t^{BESS} = S_{BESS}\left(c_i^{ESS} + c_{ESSm} k_{om}\right) \tag{23}$$

In equation (21-23), E^D is the energy providing by the battery (kWh), S_{BESS} is the battery energy storage system size rated in (kWh), $Cost_t^{BESS}$ is battery energy storage system cost rated in ($/kWh), c_{ESSm} is the energy storage system maintenance cost rated in ($/kWh), c_i^{ESS} is the ESS installation cost rated in ($/kWh), k_{om} is the maintenance factor, and ρ is the battery state of charge.

G. Dg and Grid Constraints

Since utilities incorporate their system components based on the load demand, they constantly sign peak demand contracts with consumers. Any request beyond the requirements of this contract result as a consequence of fines or loss in power connection. In the same way, diesel generators cannot meet loads exceeding their rated capacity. The supply of power limitations is considered for the diesel generator and the grid connection by expressions (24-25).

$$P_{(min)}^{G} \leq P_{(t)}^{G} \leq P_{(max)}^{G} \tag{24}$$

$$P_{(min)}^{DG} \leq P_{(t)}^{DG} \leq P_{(max)}^{DG} \tag{25}$$

H. Energy Participation Among Grid and Prosumer

The grid net energy (E_n^G) traded with the utility in a single day is as follows: the energy import from the utility and the energy exchange to the utility are signified by the values of positive and negative of $P_{(t)}^G$, respectively.

$$E_n^G = \sum_{t_1}^{t_{24}} P_{(t)}^G \times h \tag{26}$$

I. Stochastic Modelling of Solar Pv

The generation of photovoltaic solar energy is very irregular and depends on the climate and output of solar irradiance. Under random conditions, the data of the whole year will be analyzed. This article uses the solar irradiance model that has already been developed [58]. It also computes the parameters for the probability density (PDF) function of the standard normal distribution. By using Latin Hypercube (LHS) general sampling technique, 365 scenarios can be generated in 24 hours [59]. With the purpose of reduction in the calculation or computation burden, as mentioned in [60], the fast-forwarding technique is used to lessen the number of random scenarios generated upto almost 40 [60].

$$F_0 = \frac{1}{\sigma\sqrt{2\pi}} e^{-\left(\frac{1-\mu}{2\sigma^2}\right)^2} \qquad (27)$$

$$P_{(t)}^{PV} = \eta_{PV}, j\alpha_{PV} I \qquad (28)$$

The normal distribution function [61] mentioned in equation (27), is used to create an uncertainty model related with solar irradiance. Where $\eta_{PV}; j;$ I and α_{PV} are the efficiency of the solar panel (17%), the solar irradiance pattern (kW/m$^{2)}$, and the area of the solar panel (m^2) respectively while μ and σ represent the mean and standard deviation of normal distribution, respectively. Equation (28) shows the output solar power P_t^{pv}, which is relied on the solar irradiance of an exact area. Figure 3 shows the standard and mean deviation values of the solar irradiance regular pattern for the Taxila region in which the campus μG that has been taken into consideration is located there. The latitude and longitude of the Taxila region is "33.746◦N" and "72.839◦E", respectively, that is 5.3 kWh/ m2/day [62].

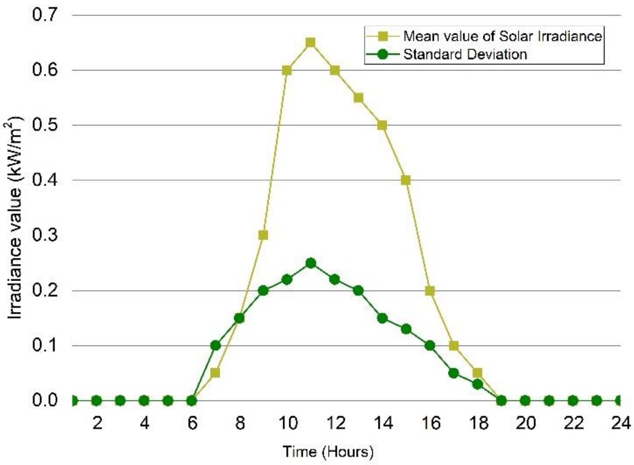

FIGURE 3. Standard deviation and mean value curves.

J. Energy Participation Among Grid and Wind Turbine

The wind power output $P_{(t)}$ traded with the utility grid is expressed in equation (29) as:

$$P_{(t)} = \left\{ \begin{array}{c} 0\,, V_{(t)} < V_{ci} \\ P_r^{WT} \times \left(\frac{\nu_w - \nu_{ci}}{\nu_r - \nu_{ci}}\right), v_{ci} < v_{(t)} < V^r \\ P_r^{WT} + \left(\frac{Y_w - V_r}{V_{ci} - V_r}\right) \times (P_{co}^{WT} - P_r^{WT}) \\ , v_r < v_w < v_{co} \\ 0, \qquad v_{co} < v_w \end{array} \right\} \qquad (29)$$

The minimum cut-in speed required by the WT to generate power is expressed as (ν_{ci}). The maximum cut-out speed at which maximum power is allowed to be generated is given as (v_{co}), if this speed is exceeded to avoid WT damage, then turn it off.

K. Levelized Cost of Energy (LCOE)

In order to conduct a fair and an effective economic analysis of the system, the levelized energy cost is measured in multiple scenarios. It is denoted as the ratio between the entire system installation cost ($) and the energy produced (kWh). The LCOE for a storage or specific energy is expressed in $/kWh. It fulfills all related costs, consist of installation costs, operational costs, maintenance costs, and capital costs. It can also be observed as the minimal cost at which an electrical power should be sold during the life of the power generation or storage component to achieve balance or to attain breakeven point. [63]. Mathematically, LCOE formula can be given as:

$$\text{LCOE} = \frac{Lifecycle\ cost(\$)}{Life\ time\ energy\ production\ (kWh)} \qquad (30)$$

L. Solution Methodology

Since the objective function and all related constraints of the proposed system model are basically the linear models with so many other integer variables, however, MILP programming is integrated to solve a linear optimization problem. The MILP technique is a common worldwide optimization method used to solve various kinds of optimization problems that is linked with marketing, scheduling, and optimal scheduling [64]. Moreover, it is also compared to many metaheuristic methods that provide suboptimal outcomes, but MILP provides the best optimal solutions and results. Hence, MILP method is extensively used in the EMS optimization [65]. The generic structure of MILP is given as follows:

$$\min_{\boldsymbol{x}} f^t x \qquad (31)$$

$$t_0 \left\{ \begin{array}{c} B.x \leq b \\ B_{eq}.x = b_{eq} \\ xb \leq x \leq yb \end{array} \right\} \qquad (32)$$

In equation (32), xb; yb; x; b; b_{eq}; and f are vectors, where B_{eq}; B is a matrix. Figure 4 shows the general flowchart diagram to control the proposed campus μG. In the initial stage, all the input data that is essential for the day is loaded one hour before each day arrival. Data includes forecasted irradiance, forecasted temperature, load patterns, the ESS initial condition, TOU tariff information, and its associated parameters. The simulation of the given optimization model is based on some regular interval prior to use of every single hour. However, the proposed algorithm is basically simulated in MATLAB software, version-R2017a with Intel

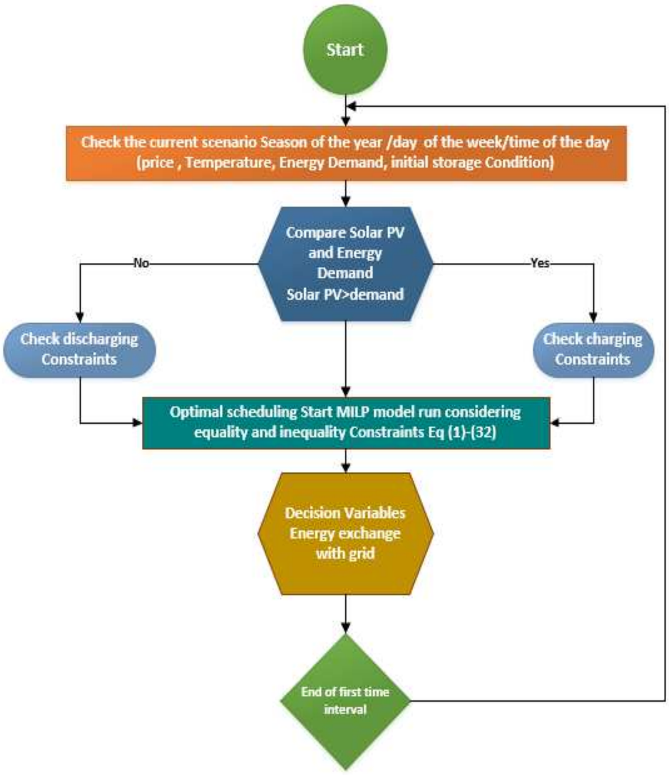

FIGURE 4. Proposed methodology of the given solution.

(R) Core (TM) i7-7700 @ 2.80 (GHz) processor with an 8GB RAM.

IV. RESULTS AND DISCUSSION:

The given model is implemented for the prosumer microgrid in section 3 located in the Punjab province. The university has eight hostels, fourteen departments and six faculties. At present, the university is feeding its load from 2MW grid connection. The capacity of the campus rooftop PV installation is calculated to be 4MW from a brief analysis of the area available for the campus rooftop.

According to the NEPRA (National Electric Power Regulatory Agency, Pakistan) which permits only 1MW energy trading among the utility grids, therefore we have limitation in installing 4MW PV due to regulatory requirements and budget constraints. In our case, the distributed generation optimal sizing is also focused now as compared to the [5], an onsite 2 MW solar PV installation is considered for comprehensive technical and economic analysis. Some other effects also focused here to utilize the available diesel generator as a backup in case of power grid failure.

In addition, it is expected that the power grid has an efficient net-metering facility which allows power export regulation up to 1MW to overcome the prosumer energy consumption cost. The campus load varies continously because of the loads of hostel, academic blocks, administration offices, and housing colony inside the campus.

The implementation of solar PV in Pakistan is a feasible and workable solution to mitigate the energy crises; according to the [66] report, Pakistan producing 5100 kWh solar energy from 1 MW solar plant per day. Thus, we have devised a solution in this work 320 sunny days/ year and 9 sunlight hours/ day. Furthermore, a BESS system has also been considered for our approach. Since by implementing a PV system for the campus μG, lithium ion batteries are proposed with the advantages of their long lifetime, superior efficiency, healthy energy density, high reliability, and low self-discharge [9].

A. CASE STUDY

In this case study, an optimum scheduling of microgrid is introduced for two main seasons; summer and winter in Pakistan. Variations in load patterns are observed typically for both the seasons and for the ease in analysis both the patterns are considered same for both the seasons respectively.

In Pakistan, January and August are the peak energy consumption months, as these are considered to be the peak load months [67]. Peak load patterns for both the months (January and August) are taken for economic analysis while considering worst-case scenarios. To analyze the economic benefit, energy generated from PV can be exported to the utility to gain maximum benefits. The actual energy consumption of the campus is considered for the typical days and to analyze the electrical energy cost on regular bases, the data is taken from the local substation meters. The load variation patterns are observed for both winter and summer seasons as shown in Figure 5, whereas the load distribution patterns among hostels, academic block, and residential block is illustrated in the Figure 6.

TABLE 2. Optimal sizing system parameters.

Parameters	Value	Parameters	Value
P^{PV}_{rated}	2000kW	C^{ES}	800kWh
$P^{G}_{(t,\max)}$	2000kW	$P^{G}_{(t,\min)}$	-1000kW
$P^{bat}_{(t,\max)}$	800kW	$P^{bat}_{(t,\min)}$	-800kWh
$BSOC^{b}_{(\max)}$	90%	$DOD^{b}_{(\max)}$	0.95
$BSOC^{b}_{(min)}$	50%	Battery Lifetime (LTY)	10
BESS Fix-price (FB)	70.875	SOHM	0.6

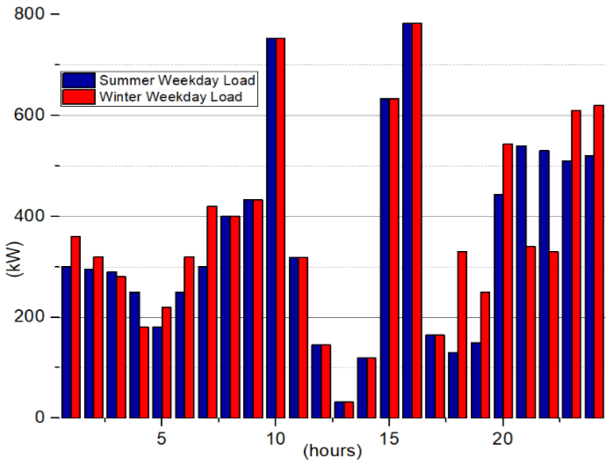

FIGURE 5. Campus load patterns of summer weekdays and winter weekdays.

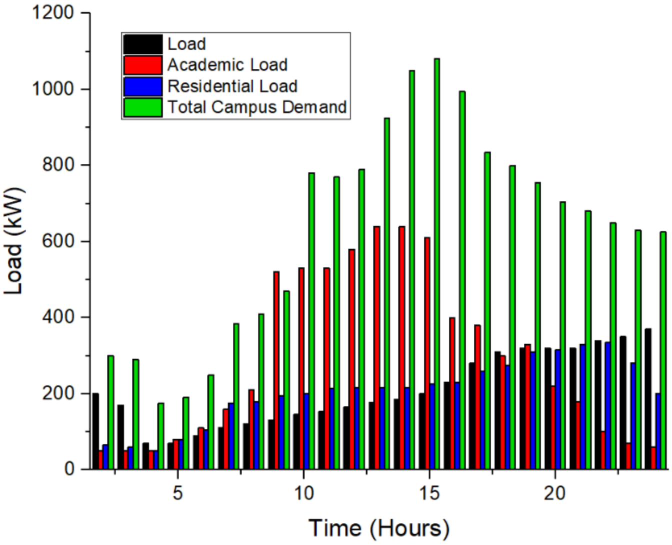

FIGURE 6. Load distribution patterns among campus energy.

The loads of admin and academic blocks are set to be high when campus is on, while the peak demands of energy in the hostels and the residential colony are observed till midnight. Table 2 signifies multiple parameters that are interlinked with the system, whereas electricity price information of the TOU scheme is described in Table 3 [68]. The detailed data of solar irradiance used here is taken from [69], and the data characteristics are modeled and analyzed using probability distribution function (PDF) that is already mentioned in equation 19. The main objective of PDF is to produce the solar irradiance pattern regularly on daily basis, while solar irradiance pattern that is generated earlier estimates the PV generation output power using equation (20), whereas Table 4 describes the case study profiles.

B. SUMMER SEASON CASE

In the summer season case, the exchange investigation and energy consumption are discussed here with the help of price-based data mentioned in Table 3. Multiple scenarios have been devised here to understand the energy demand for both the seasons.

Scenario 1, (a): In the first scenario, the power demand for the campus is provided completely from the grid. No PV, wind, ESS and the diesel generator are available here for the campus. With the help of time of use (TOU) tariff, operational cost of energy is found out to be $1430.8. The LCOE is calculated here 0.0988$/kWh, in this case. The outcome of the results indicated that the energy day-to-day operational cost is extremely high in the first scenario and this will be used as a case study for comparing and analyzing with other case scenarios for the summer season.

Table 3. Electricity price distribution per unit.

Summer Season		Winter Season	
Timing (hours)	**Unit Prices ($)**	**Timing (hours)**	**Unit Prices ($)**
12:00 AM to 7:00 PM	0.10	12:00 AM to 6:00 PM	0.10
7:00 PM to 11:00 PM	0.138	6:00 PM to 9:00 PM	0.138
11:00 PM to 12:00 AM	0.10	9:00 PM to 12:00 AM	0.10

Table 4. Case studies profiles.
Table 5. Case (1) Summer results.

Case 1	Power Load	Only Grid	Solar PV	ESS	DG	Wind	Power Load	Case 2	Only Grid	Solar PV	ESS	DG	Wind
(a)	Summer Load	✓	×	×	×	×	Winter Load	(a)	✓	×	×	×	×
(b)		✓	✓	×	×	×		(b)	✓	✓	×	×	×
(c)		✓	✓	✓	×	×		(c)	✓	✓	✓	×	×
(d)		✓	✓	✓	✓	×		(d)	✓	✓	✓	✓	×
(e)		✓	✓	✓	✓	✓		(e)	✓	✓	✓	✓	✓

Case 1	Only Grid	PV	ESS	DG	Wind	Energy import by Grid (kWh /day)	Electricity generated from Prosumer (kWh /day)	Grid electricity net cost/day ($) *	CC** ($/ day)	Electricity Net Cost without CC/day ($)[1]	Electricity Net Cost CC/day ($)	LCOE ($/kWh)	% Saving
									A	B	C=B-A		
(a)	✓	×	×	×	×	14472.5	-	1430.8	-	1430.8	1430.8	0.0988	-
(b)	✓	✓	×	×	×	5546.8	8925.7	610.7	165	963.5	798.5	0.055	43.6
(c)	✓	✓	✓	×	×	5546.7	8925.7	711.5	165	984.9	819.9	0.056	42.8
(d)	✓	✓	✓	✓	×	4983.2	8925.7	768.2	155	970.5	843.5	0.058	40.2
(e)	✓	✓	✓	✓	✓	4763.2	9295.9	546.4	145	.995.9	850	0.060	38.3

*This includes the grid electricity cost only without the cost of other components involved here such as ESS, WT, PV and/or DGen

[1] This cost is found out by calculating the LCOE for each scenario. LCOE from PV is taken as 0.048$/kWh [5]. The proposed given model already incorporated the O&M costs of ESS and/or DGen in their relevant scenarios, therefore, the installation costs of DGen and ESS is slightly offset by adding 0.15$/kWh and 0.06$/kWh, respectively [70].

**Carbon Credit (CC) assuming that the prosumer is registered under the carbon development mechanism (CDM) [5].

Scenario 1, (b): In the second scenario, the solar PV is combined with the prosumer microgrid, it is integrated to export the surplus energy to the utility as well as feeding the load. The solar PV generates 8925.7 kWh that signifies the efficacy of PV in the summer season. The LCOE taken for the solar PV is 0.055 $/kWh here. However, the electricity net cost per day is reduced by 43.6% which becomes $798.5 from the base value. Scenario 1, (c): In the third scenario, ESS is integrated with the PV and utility connection. The proposed approach is implemented to find the net energy cost that is $819.9 obtained and to optimal schedule the battery charging/discharging patterns optimally with the consideration of all associated components of costs in this third scenario. The LCOE calculated to be $ 0.056/kWh with the help of TOU based tariff while considering BESS optimal scheduling as mentioned in the Table 5. The minor increment in the LCOE is because of BESS cost that is involved here in this scenario. The comparison with the base scenario 1(a) reveals that it reduced the net cost of electricity about 42.8%. The energy trade with the utility grid is also indicated in the Figure 7 in which +ve and -ve values signifies the energy import and export. The ESS optimal scheduling result shows that the battery end operation at the same amount of SOC i.e., it operates 50% exactly according to the day begins. Moreover, the ESS wisely save the surplus energy in off-peak and peak hours, it discharges accordingly to reduce the operational cost of energy as showing in the Figure 8.

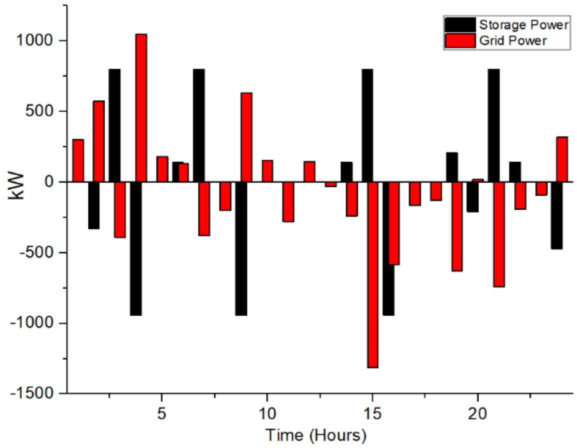

FIGURE 7. Case 1, (c): Energy exchange with the power grid.

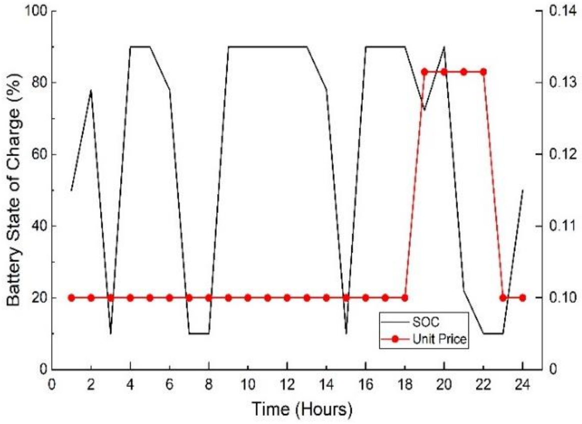

FIGURE 8. Case 1, (c): State of charge of a battery with TOU tariff.

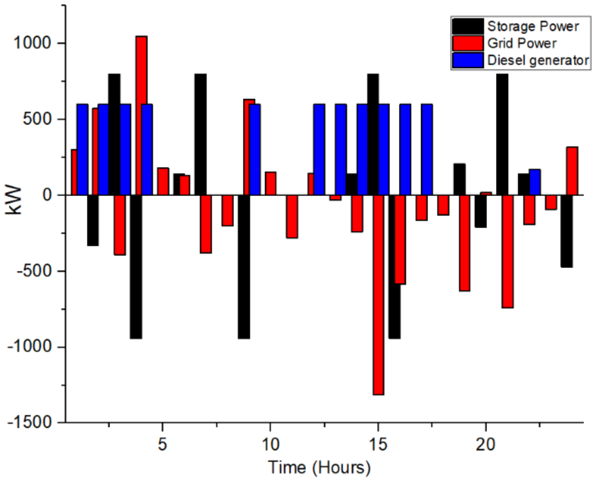

FIGURE 9. Case 1 (d): Energy exchange with the grid.

Scenario 1, (d): In the fourth case, the campus microgrid integrates the diesel generator (DGen) with solar PV and the BESS system to reduce the peak consumption power from grid during (7:00 PM to 11:00 PM) for summer season. The grid imports energy maximum up to 50kW that is the limitation for the grid connection and the limitation for output power of the DGen is set to be 600 kW through these peak hours, as seen in Figure 9.

After BESS optimal scheduling, the electricity net cost is found out to be $ 843.5 per day. The LCOE calculated, in such case, is 0.058 $/kWh which is then compared with the base scenario 1(a), it is found out that it is 40.2% less with the 3.517600 seconds execution/computational time for the summer season.

Scenario 1, (e): In the proposed scenario, the wind turbine system (100kW) is incorporated with the ESS, Solar PV, Diesel Generator and the grid connection. The wind power and wind speeds tend to be (3-5) times higher in March month and

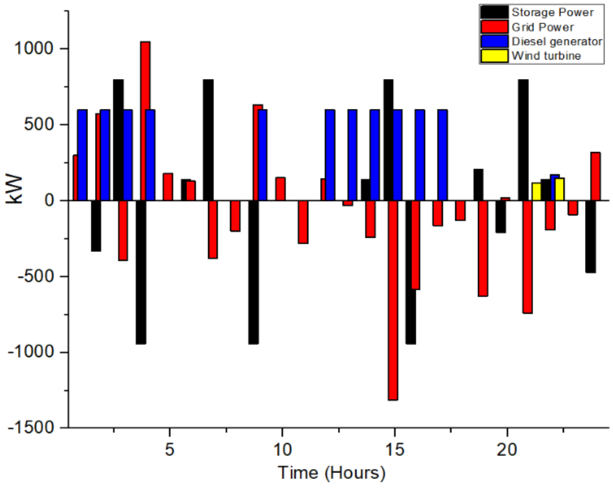

FIGURE 10. Case 1 (e): Energy exchange with the grid.

April month. The campus μG considered rated power of wind to be 25kW while considering various factors in which, hub height is 36.6m, rated speed of wind is 14m/s, wind cut-in speed is 3.5 m/s, and wind cut-out speed is 25 m/s is the better choice amongst the wind turbine considered. The LCOE calculated for the wind to be 0.060 $/kWh which is 38.3 % less as compared to the 35% [5] for the summer season. It is analyzed with the integration of WT system with ESS, Solar PV, Diesel Generator and the grid connection, 3% saving increased in the electricity net cost for the UET Taxila campus.

C. WINTER SEASON CASE

In winter case, the average demand of the load is comparatively bigger as in comparison with the summer season, so an intelligent and efficient optimal scheduling is required to fulfill the load. In the winter weekdays, the administrative offices and academic blocks are all operating normally and the load demand crosses the peak limit beyond 1 MW. Various scenarios are considered here as a case study that are mentioned below.

Scenario 2, (a): By comparing it with scenario 1(a) of summer season, the overall energy utilization is fulfilled from grid during winter scenario. During winter season, we consider TOU-based tariffs to calculate the utility electricity bills. No DGen, BESS or PV or are examined in case (a). Due to increase in the load volume of winter, the result obtained is $1,710.4, which is comparatively higher than the case 1(a) in summer. This TOU-based scenario is acted like a base case for winter.

Scenario 2, (b): In the second case scenario, we assume that a 2MW photovoltaic solar plant is installed on the on-site roof facility of a campus department incorporated with a net metering environment that able to exchange the energy with the grid. The excess power will be immediately traded with the community grid without any scheduling. The electricity net cost is minimized to $1075.5, a total reduction of 37.7% compared to the base scenario of case (a) with a cost of $1,710.4. The reason for the lower net cost is that photovoltaic solar power generation is cheap. Though, it depends on the availability of the utility grid and mostly on the weather conditions. During grid outages or cloudy days, this scenario cannot provide continuous power. Therefore, in the following cases, DGen and ESS are further added to investigate its effects.

Scenario 2, (c): Based on the TOU tariff shown in the Table 3, the determined peak load demand hours are from 5:00 P.M to 9:00 P.M for winter season. In this case, battery energy storage is further included to improve the flow of energy trade among the utility grid. The net cost of electricity fell from $ 1,710.4 to $1102.3, which is a 36.1%, decrease from base case 2, (a). The recommended scheme is employed to optimize the ESS charging and discharging to gain economic benefits, as showing in the figure 11. Although the electricity cost of the grid is decreased in this case due to the fixed optimizer, when you try to trade power to the utility grid in peak hours with the help of ESS, the electricity net cost is even high in this case scenario 2 (c) due to the installation costs, maintenance costs, and operational cost of BESS. The general comparison shows that the decrease in the percentage of LCOE is 40% compared to baseline scenario 2(a).

Scenario 2, (d): In this scenario, it is assumed that there is an on-site diesel generator available in the campus μG to stretch the utility grid in relax mode during peak hours. The energy import from the grid is limited to 50 kW. An additional DGen is further incorporated into the system to constantly supply the power in the event of a grid failure. Figure 12 shows the battery's state of charge, indicating the ratio of available energy to total capacity.

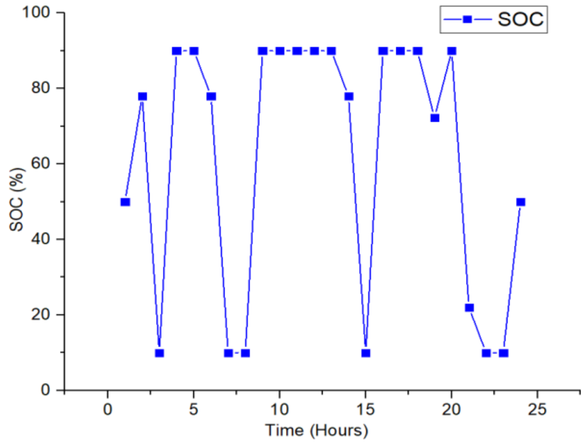

FIGURE 11. Case 2(c): State of charge of a battery.

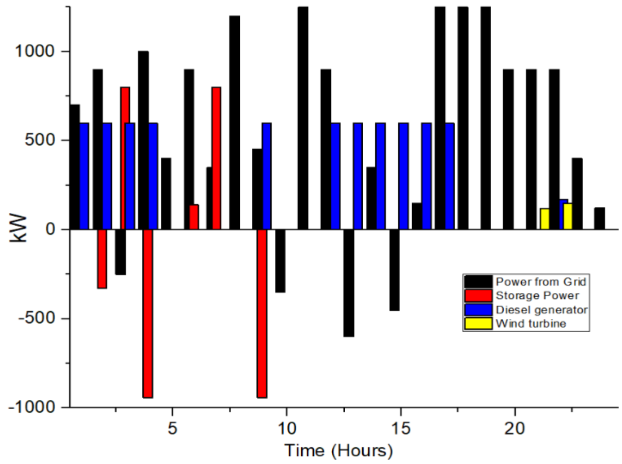

FIGURE 12. Optimal Scheduling of the proposed solution in case 2, (d).

The red bar in the Figure 12 shows input power of the storage, where blue bar signifies DGen activity when the grid network is in relax mode during peak hours.

While the daily operating cost of grid recorded in this scenario is $1147.1, which is more of 32.4% higher compared to $1102.3 that is noted in previous case scenario 2, (c), this increment is insignificant as compared with the previous obtained network stability. The execution/ computational time recorded is 3.596252 seconds for the winter season. After all the analysis and discussions, scheduled ESS and solar PV combined with the utility grid is an optimum and best solution for cost minimization compared to this case. Whereas, the Figure 12 shows a comparison of summer and winter cases. All the winter case studies results are presented in Table 6. Table 7 illustrates the comparison of the given model.

Scenario 2, (e): In the proposed scenario, it is assumed that a wind system is integrated in winter season with the Solar PV, Diesel Generator, ESS, and the grid connection. The wind speeds and wind power have a tendency to be increased again in September and November months. The campus µG considered rated power of wind to be same as compared to the summer season. The LCOE calculated for the wind to be 0.0703 $/kWh which is 31.3 % less as compared to the 29% [5] for the winter season. It is analyzed with the integration of WT system with ESS, Solar PV, Diesel Generator and the grid connection, 2.3 % saving increased in the electricity net cost for the UET Taxila campus. The proposed scheduling patterns of overall campus output power is shown in the Figure 13.

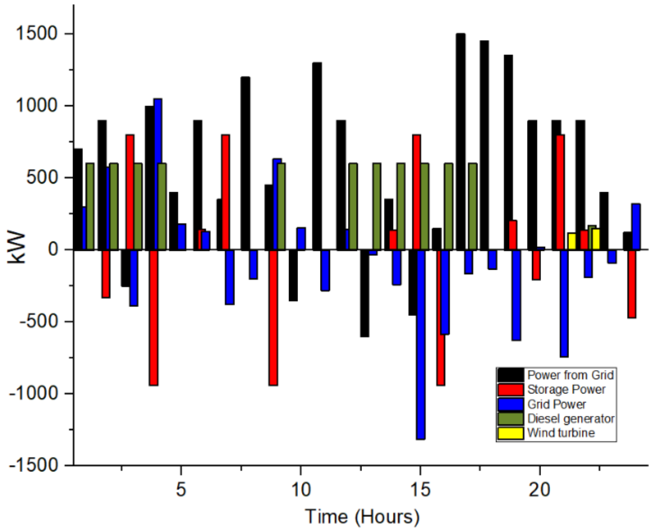

FIGURE 13. Proposed Optimal Scheduling in case (e)

D. EFFECTS OF SIZING OF SOLAR PV ON ENERGY COST AND REDUCTION OF CARBON EMISSIONS

The effects of multiple sizing of solar PV incorporation in prosumer µG on the cost of purchasing energy from the grid and the reduction of CO2 emissions per day are analyzed. When solar integration doubled, GHG emissions also minimized two times as well as with the cost reductions and is briefly shown in Table 8.

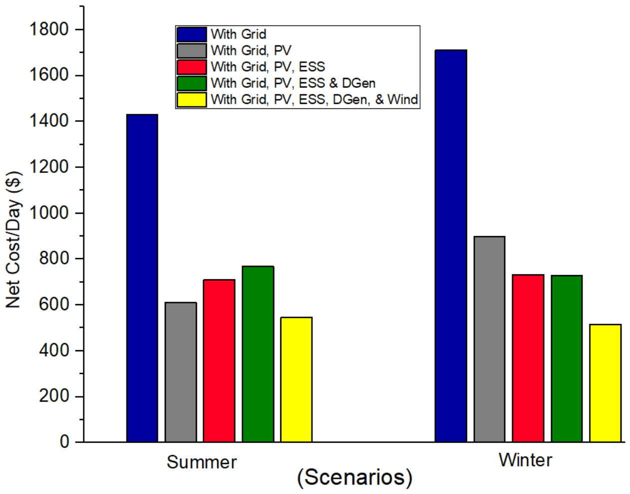

FIGURE 14. Analysis of summer and winter cost scenarios.

The bar graph in Figure 15 also illustrates the various types of PV integration in the given model and their impact on the electricity cost that is purchased from the utility.

Based on the obtained values in the above-mentioned cases, we can examine the difference in the operating cost of energy.

The analysis demonstrates that integrating distributed generation systems has numerous benefits, including self-consumption, load flexibility, cost reduction, and reduced of GHG emissions. As a result, the proposed method can be integrated to minimize the operating cost of campus electricity consumption. It basically requires a control facility to optimally control all types of sources and loads. In addition, offloading the grid also improves grid efficiency through the integration of renewable energies. Capital and

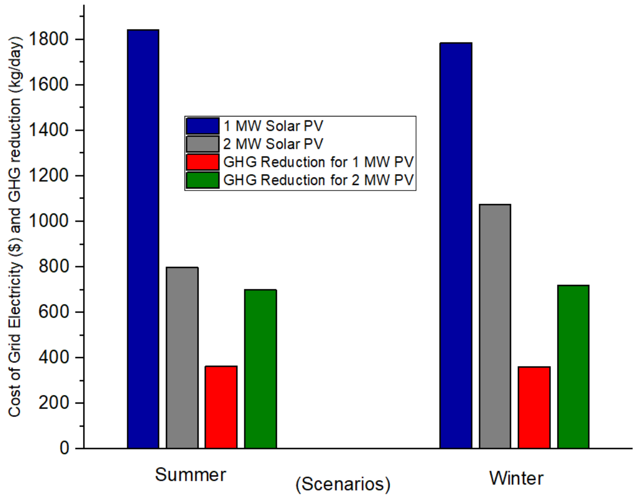

FIGURE 15. Analysis of PV sizing of Solar and reduction of GHG.

TABLE 6. Case (2) Winter results.

Case 1	Grid Only	With PV	With ESS	With DG	With Wind	Utility Grid Energy Import (kWh/day)	Energy produced from the prosumer end (kWh/day)	Electricity grid cost /day ($) *	CC** ($/day)	Electricity net cost without CC/day ($)[1]	Electricity net cost with CC/day ($)	LCOE ($/kWh)	Saving in %
									A	B	C=B-A		
(a)	✓	×	×	×	×	16849.9	-	1,710.4	-	1,710.4	1,710.4	0.102	-
(b)	✓	✓	×	×	×	8254.7	8595.2	897.3	169	1244.5	1075.5	0.064	37.7
(c)	✓	✓	✓	×	×	8254.6	8595.2	732.7	169	1271.3	1102.3	0.065	36.1
(d)	✓	✓	✓	✓	×	7989.7	8595.2	728.8	154	1301.1	1147.1	0.069	32.4
(e)	✓	✓	✓	✓	✓	7641.5	8883.2	516.3	127	1288.9	1161.9	0.0703	31.3

*This includes the grid electricity cost only without the cost of other components involved here such as ESS, WT, PV and/or DGen

[1] This cost is found out by calculating the LCOE for each scenario. LCOE from PV is taken as 0.048$/kWh [5]. The proposed given model already incorporated the O&M costs of ESS and/or DGen in their relevant scenarios, therefore, the installation costs of DGen and ESS is slightly offset by adding 0.15$/kWh and 0.06$/kWh, respectively [70].

**Carbon Credit (CC) assuming that the prosumer is registered under the carbon development mechanism (CDM) [5].

TABLE 7. Comparison of the existing works compared with the proposed method.

Ref.	Year	Application	Technique	Remarks	Savings
[20]	2017	IEEE-14 bus system	BBSA	Reliability, Power losses	18.26%
[13]	2018	Campus µG	MILP	ESS Degradation Cost, Peak Demand	5.32%
[17]	2018	IEEE-15 bus system	NA and Conic Technique	Financial Feasibility	3.3%
[19]	2018	Residential Level	MILP	Frequency regulation	7%
[14]	2019	Residential µG	LP	Grid outage	16%
Proposed Model	2021	Campus µG	MILP	Self-Consumption, ESS Degradation, Demand response, Optimal sizing & Economic analysis	31.3%, 38.3%

installation costs will be allocated in some cases, which will incentivize campus stakeholders to put more money in battery installation and DG.

E. EFFECT OF LOADING CONDITIONS ON ELECTRICITY COST/DAY AND LCOE

Load consumption models are used for economic analysis and respectable savings relying on peak energy consumption. However, the effect of the load change is also observed on the electricity net cost per day and LCOE. For that kind of reason, the lower, regular and peak consumption load days for the summer and winter seasons are investigated with the optimal scheduling of campus µG with grid connected PV, DGen, and ESS. The results found for various load conditions utilizing 2000 kW solar PV installations throughout summer and winter seasons are shown in Table 9.

The energy imported from the utility is 3545.2 kWh per day for the lowest energy usage in the summer season, however the electricity net cost is $553.7 per day. Due to the lowest energy consumption, the LCOE obtained is $0.044 per kWh.

On a hot summer day, the average load consumption is higher, and the energy import from the utility is more than on the day with the lowest energy consumption. In this average load consumption case, the electricity net cost and the LCOE obtained are $697.6 and $0.050 per kWh, respectively. During the peak load consumption case in summer, the electricity net cost increases to $798.5 per day, while the LCOE rises to $0.055 per kWh.

Similar results for LCOE and electricity net cost for different winter load modes are also given in the Table 9.

TABLE 8. Case study profiles of PV Integration for both summer and winter seasons with multiple ratings.

Case	Solar PV Penetration level	ESS and Grid	Electricity import by Grid (kWh/day)	Electricity generated from solar PV (kWh/day)	Grid electricity net cost/day ($)	GHG reduction (kg/day)
Summer	1000kW	✓	10037.23	4462.85	1843.20	365.34
	2000kW	✓	5546.8	8925.7	798.5	700.68
Winter	1000kW	✓	11866.58	4297.6	1785.4	362.23
	2000kW	✓	8254.7	8595.2	1075.5	720.46

TABLE 9. Load variation effects on electricity cost and LCOE.

Season	Pattern of load consumption	Electricity import by Grid (kWh/day)	Electricity generated from solar PV (kWh/day)	Grid electricity net cost/day ($)	LCOE (S/kWh)
Summer	Lowest	3545.2	8925.7	553.7	0.044
	Average	4986.3	8925.7	697.6	0.050
	Peak	5546.8	8925.7	798.5	0.055
Winter	Lowest	5207.9	8595.2	670.74	0.048
	Average	7290.8	8595.2	956.37	0.060
	Peak	8254.7	8595.2	1075.5	0.064

F. ECONOMIC EFFECTS ON OPTIMAL BESS SIZING

The Table 10 demonstrates the techno-economic analysis data with different components used for the proposed system and it covers all the maintenance, operational, and capital costs of the proposed system.

The analysis also demonstrates the system components power ratings, Capital costs, replacement costs, operation and maintenance costs, payback period, system efficiency, and their lifetime.

The objective components include solar PV, BESS, converter, wind turbine, DGs, grid, and other extra equipments that include in the microgrid system.

Table 10. Techno-economic data associated with the different components of the proposed system.

Sr No.	Objective Components	Objective Parameters	Value	Unit
1	Solar PV	Photovoltaic Power Rating	1	kW
		PV Capital Expenses	933.33	$
		PV Replacement Cost	800.00	$
		Operation and Maintenance Cost	13.33	$/kW
		Derating Factor	88	%
		Photovoltaic Life	20	years
		Payback Period	2.88	years
2	Converter	Power Rating	1	kW
		Capital cost of the converter	133.33	$
		Replacement Cost of the converter	106.67	$
		Operation and Maintenance Cost	160	$/kW
		Overall Converter Efficiency	90	%
		Converter Life	20	years
3	BESS	Battery Capital-Cost	133.33	$
		Replacement Cost	56.00	$
		Capacity Investment Cost	240	$/kWh
		Operation and Maintenance Cost	1.33	$
		Size of the unit battery	5	kW
		Battery Rated voltage	6	Volt
		Minimum SOC	30	%
		Maximum SOC	100	%
		Efficiency	95	%
		Life of Battery	5	Years
		Payback Period	4.88	Years
4	WT	Wind Turbine	1	kW
		WT Capital Expenses	15000	$
		WT Replacement Cost	800.00	$
		Operation and Maintenance Cost	13.33	$/kW
		Derating Factor	88	%
		WT Life	20	Years
5	DGs	Capital Expenses	9467	$
		Replacement Cost	28.35	$
		Operation and Maintenance Cost	2449.5	$/kw
		Efficiency	80	%
		Life	25	year
6	Grid	Supply Cost	10	$
7	Other	Rate for discount	6	%
		Life of Project	20	year

The effects of various system components that are already running in the system analyzed. The system NPV cost are analyzed with different components combined in the system. It is analyzed that the system with 2000 kW solar PV, 600kW DG, 6000kWh Li-ion battery capacity, and 1200 rating converter has the 13.1M $ net present cost for the system. If the system utilized components with ratings 3000kW solar PV, 700 kW generator, 7000kW BESS, and

1400kW converter, then the net present cost analyzed 15.6M $ approximately.

Net present cost (NPC) for different components ratings are analyzed below:

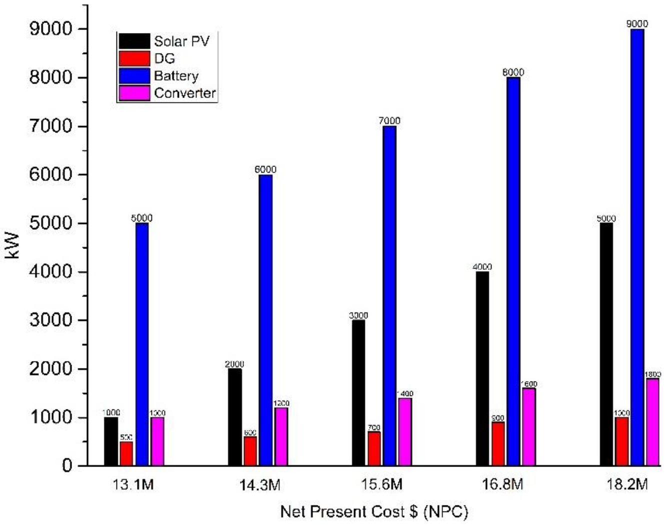

FIGURE 16. Net present cost for different components used in the system.

The system Cost of Electricity (COE) is also compared and analyzed with other components of the system; it is compared that the system with having generator has COE value is comparatively higher. However, for the system of 2000 kW solar PV, 600kWDG, 6000kWh Li-ion battery capacity, and 1200 rating converter, the COE analyzed for the system 0.10$ for off-peak and 0.138$ for peak hours. For the system, 3000kW solar PV, 700 kW generator, 7000kW BESS, and 1400kW rating converter, the COE calculated to be 0.12$ for off-peak and 0.138$. Cost of Electricity (COE) for different ratings of PV, DG, BESS, and converter are analyzed in figure 7:

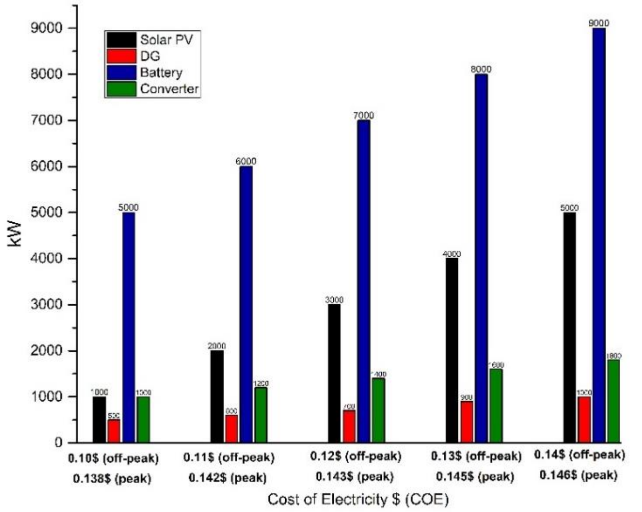

FIGURE 17. Cost of Electricity (COE) for different components.

However, an optimal BESS solution has been selected for the U.E.T Taxila in the microgrid system as an optimal solution of 8925.7 kW of PV, 600 kW of DG, 25 kW of WT, and with 5000kW BESS system for summer, and vice versa. An optimal system is adopted for the campus microgrid by calculating 850$/kWh as a daily electricity cost which is an optimal solution for summer, whereas, 1161.9$/kWh is an optimal case in case of winter. However, savings analyzed with the previous case scenarios [5] that 38.3% savings analyzed for summer, comparatively 3.3% higher than the previous case scenario and 31.3 % saving analyzed for the winter case, comparatively 2.3% higher than the previous case. It is analyzed that the optimal BESS solution with the incorporation of WT system, savings are analyzed comparatively higher which is best possible solution for the university campus microgrid.

V. CONCLUSION

In this study, an optimal scheduling of ESS and the impacts of solar PV are studied on a campus μG to lessen the energy operating costs for a commercial prosumer with the help of real load data. The proposed system considered solar PV, battery storage systems, and diesel generators under multiple scenarios, and it analyzed their effects in various conditions. The optimal scheduling problem was simulated in MATLAB and modelled in a mixed integer linear problem considering battery life into account. The TOU based tariff (price based-DR) was studied here and ESS is employed as a flexible DR system that could be charged and discharged intelligently at various timings to fulfil the objective of cost reduction without affecting its durability. Without ESS or DG, all the required energy of the campus μG is provided by the utility company, resulting in increased operating costs. But when PV, WT, DGen, and ESS are incorporated with the prosumer μG, the percentages of daily savings are 38% and 31%, respectively, in summer and winter. The environmental impact of multiple sizes of PV installations is also studied here, and it has been found that around 365.34 and 362.23 kg CO2 / day can be conserved by the installation of 1000 kW solar PV, in summer and winter. If 2000 kW solar PV is included in the system, this savings increases by 700.68 and 720.46 kg/day in summer and winter, respectively. The reduction in the cost of electricity depends on various parameters such as demand, feed in tariffs (FIT), locations etc. In Pakistan, the FIT has similar costs of buying and purchasing of electricity similar to those in many countries while the cost of selling the electricity to the utility is comparatively lesser than the cost of buying the electricity from the utility. As a result, investors can expect their electricity costs to increase by 20-30% by investing in on-site PV and ESS systems on an optimal schedule based on FIT, location and level of their load consumption. This leads to the conclusion that the optimum charge-discharge strategy for the ESS plays an important part in the economic performance of prosumer buildings with internal RER installations. DG uncertainty, with more complex mathematical models with several storage systems taking into account DR types as well as a sensitivity analysis will be analyzed in future work.

DECLARATION

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Not applicable

CONSENT FOR PUBLICATION

Not applicable

AVAILABILITY OF DATA AND MATERIALS

The research material that are analyzed and implemented in the current study are available on the reasonable request.

COMPETING INTERESTS

The authors declared that they have not any competing interests.

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AUTHORS' CONTRIBUTIONS

Muhammad Shahzad Pansota[1] supervise the whole project. Haseeb Javed analyze the real-time-based campus load consumption data and simulated on MATLAB to calculate energy consumption behavior. Hafiz Abdul Muqeet also helped in optimizing the results. M Irfan on the other hand, helped in improving the quality of the paper. Moazzam shehzad helped in analyzing the whole research and giving specific solutions while Rehan Liaqat also contributed in giving suggestions in attaining optimized results.

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