2024 IEEE 4th International Conference on Sustainable Energy and Future Electric Transportation (SEFET) | 979-8-3503-8399-7/24/$31.00 ©2024 IEEE | DOI: 10.1109/SEFET61574.2024.10717922

Optimizing Microgrid Operations with Risk-Based Energy Management System*

1st Debasmita Panda
Department of Electrical Engineering
National Institute of Technology Warangal
India
dpanda@nitw.ac.in

2nd Altaf Q H Badar
Department of Electrical Engineering
National Institute of Technology Warangal
India
altafbadar@nitw.ac.in

***Abstract*—Risk-based microgrid energy management refers to the strategy of managing the operation and control of a microgrid while considering various risk factors associated with its components and external factors. Microgrids are localized energy systems that can operate independently or in conjunction with the traditional grid, typically incorporating renewable energy sources, energy storage systems, and advanced control technologies. However, managing a microgrid can be challenging due to the intermittency of renewable energy sources, such as wind, solar, load fluctuations, grid price and energy storage system performance. A Microgrid Energy Management System (Microgrid EMS) is a software platform designed to monitor, control, and optimize the operation of a microgrid considering the uncertainties involved.The risk contributing factors considered for this work includes, uncertain behaviour of distributed energy resources (DERs) like solar panels, wind turbines, load uncertainty and grid price. These uncertainties make microgrid operation more challenging. The paper presents a risk based microgrid EMS model that can be used to manage the integration of uncertain renewable energy sources into the main grid, which is a critical step towards achieving a more sustainable energy future.**

***Index Terms*—Microgrid EMS, Distributed Energy Resources, Smart Loads, Uncertainty handling, Mean variance analysis**

I. Introduction

In recent years, microgrid have emerged as a promising solution for addressing the challenges of integrating distributed energy resources (DERs) into the power grid. A microgrid is a localized energy system that can operate independently of the main power grid or in coordination with it. It typically includes a variety of distributed generation sources, such as solar photovoltaic (PV), wind turbines, fuel cells, and energy storage systems (ESS), along with loads like electric vehicles (EVs) & many power electronics loads. The implementation of microgrid requires the development of advanced energy management systems (EMS) that can optimize the use of DERs, balance supply and demand, ensure grid stability, and provide reliable and resilient power supply to customers. Microgrid energy management involves a range of tasks, such as forecasting renewable energy generation, managing energy storage, controlling power flow, and coordinating with the main grid.

To address these challenges, researchers and practitioners have developed various approaches to microgrid energy management, including model based and data-driven methods, optimization techniques, and control strategies. These methods have been widely used in microgrid energy management, and several studies have demonstrated their effectiveness [1] [2]. Another approach is to use robust optimization, which generates an optimal schedule that is robust to worst-case scenarios [3] [4]. However, these methods do not consider the uncertainty and variability of renewable energy sources, which can impact the reliability and cost of the system. In addition to optimization techniques, several studies have proposed using machine learning techniques, such as artificial neural networks or support vector machines, to predict the output of renewable energy sources [5]–[8].

In this paper, we focus on the development of a robust and scalable microgrid energy management system that can effectively manage the uncertainties and variability of renewable energy sources and provide reliable and cost-effective power supply to customers. The EMS framework explained here integrates advanced optimization techniques, probabilistic forecasting methods, and manages the demand-side. The paper proposes a mean-variance optimization approach for designing microgrid energy management systems (Microgrid-EMS). The objective is to maximize the expected revenue (minimize the expected cost of energy purchase) while minimizing the risk of tieline power fluctuation due to uncertain renewable energy generation and load demand. The proposed approach incorporates robust and risk-aware optimization techniques, including chance constraints to ensure reliable and efficient microgrid operation under uncertainty and variability.

II. Microgrid Energy Management Framework

A. Schematic Representation of Microgrid Energy Management System

A schematic diagram of a microgrid EMS is shown in the fig 1. The microgrid is a part of the distribution system that is connected to the main grid through a point of common coupling. Microgrid EMS is the brain of the microgrid that controls energy management within the microgrid by optimally dispatching power from the DERs, Controlling the non-essential loads and properly utilizing the storage capacity. The microgrid EMS receives load data from the customers, their load changing preferences, forecasted generation information from the DERs and grid price. Based on these information's it determines the power flow limits, utility power purchases, load dispatch, and DG/DER scheduling. The proposed microgrid

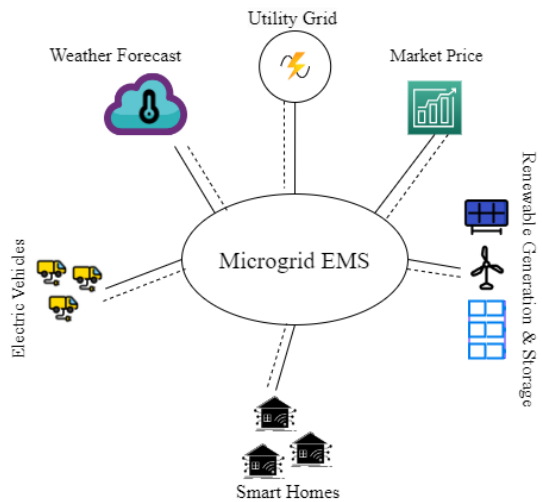

Fig. 1. Illustration of Microgrid Energy management System (EMS)

here is consists of

- Two solar PV and two wind generators as generating source
- Two load varieties as Critical and Non-Critical loads
- Two battery energy storage systems
- One point of common coupling with utility grid

The power supply to the critical loads is always guaranteed, while the power supply to the interruptible loads is based on an optimized operational solution by the MG-EMS. Critical loads may include essential services like hospitals, emergency services, few emergency industrial loads, supply to the communication networks etc. The interruptible loads include non-essential services like air conditioning, heating, and lighting in residential or commercial buildings. Advanced techniques such as demand response and load shifting are used to manage the demand-side of the microgrid.

B. Input data for the Microgrid-EMS

Data plays a crucial role in the optimal operation of a microgrid. Three essential data sources are considered for this work; 1) Day-ahead Wind and Solar power prediction, 2)Load forecasting, and 3) energy market Price. Day-ahead Wind and Solar power prediction provides an estimate of the power output from the wind turbines and photovoltaic panels for the next day. Different forecasting techniques, such as numerical weather prediction models, artificial neural networks, machine learning approaches, and statistical models are mostly used prediction techniques. The work here has used AutoRegressive Integrated Moving Average (ARIMA) a statistical analysis model for wind and solar power prediction.

Energy price is another data source that is useful for the Microgrid-EMS. Real-Time energy Price is the price of electricity in the wholesale market at any given time. Uncertainty in energy price also plays a major role in introducing risk in the planning procedure [9] [10]. Microgrid-EMS uses energy price data to optimize the operation of the microgrid, such as scheduling the charging and discharging of energy storage systems and shifting energy consumption to off-peak periods. The energy price data considered here are from historical data set. Forecasted load data are considered to model the demand side of the proposed Microgrid-EMS.

C. Uncertainty Consideration

With stochastic behavior of RE generation, load variation and grid price, more optimal risk modelling is done considering multiple scenarios of occurrence of a particular event. There are many available methods in literature for scenario generation using historical data such as k-means clustering, sampling based approach, scenario reduction technique [11]. Monte Carlo approach is another classical way to generate scenarios [12]. The risk constraint multi-objectives Microgrid-EMS modelling have two parts.

- The first part of the objective function is modelled as a financial benefit to the microgrid. It is commonly formulated as a maximization of profit or minimization of the operating cost of the microgrid over a given period of time.
- The second part of the objective function is the financial risk modelling. As per the modern portfolio theory, risk is always modelled with a 'risk aversion factor' value ranging from 0 to 1. The zero (0) value indicated that the microgrid is a risk neutral decision maker. With increasing value of risk factor, the microgrid becomes risk averse.

Mathematically, both the objective functions modelled together as a single objective functions as,

$$min \sum_{t=1}^{T} Operating\ cost(OC) + \big(\eta \times Variance(V)\big) \quad (1)$$

where, T - Total no of time periods (24 hrs.)
$Operating\ cost(OC)$ - Operating cost of the microgrid to purchase power from the main grid.
η - Risk aversion factor
$Variance(V)$ - Measure/estimates the risks by considering covariance relation between the risk factors. Var and CoVar relation between wind and PV power output is considered as risk factors in the proposed model. Variance measures the variability of PV/WT output from its mean value whereas covariance measures the degree to which these two variables change together. This interdependency between wind and PV power outputs is valuable for energy system planning, optimization, and risk management of a microgrid.

Wind power generation is characterized by its stochastic and intermittent nature, which makes it challenging to accurately predict the power output. Eq 2 below is used to describe this uncertainty range.

$$\Omega = [(1-\alpha_{w,t})P^f_{wind,w}, (1+\alpha_{w,t})P^f_{wind,w}] \quad (2)$$

where,
Ω - Uncertainty Set
$P^f_{wind,w}$ - forecasted power output of wind farm w at time t
$\alpha_{w,t}$ is the uncertainty ratio. This represents the uncertainty in the wind power calculation in relation to wind speed uncertainty. If the typical wind speed uncertainty ranges between 2-3% , as the power output is cubical of the wind speed, the wind power uncertainty ratio is taken as 20-30% [15].

Like wind power, PV power generation is also subject to uncertainties and variations due to weather conditions and shading effects. Eq 3 below is used to describe this uncertainty range.

$$\Gamma = [(1-\alpha_{pv,t})P^f_{pv,S}, (1+\alpha_{pv,t})P^f_{pv,S}] \quad (3)$$

where,
Γ - Uncertainty Set
$P^f_{pv,S}$ - forecasted power output of solar PV plant S at time t
$\alpha_{pv,t}$ is the uncertainty ratio. The uncertainty ratio for the PV power output typically ranges from 5-10% [16].

III. Problem Formulation

In the proposed MG-EMS, the objective function is to minimize both the expected operating cost and the variance of the tie-line power fluctuations simultaneously. The expected operating cost includes the cost of buying electricity from the main grid, the cost of operating the energy storage system, and the cost of any curtailment or spillage of renewable energy sources. On the other hand, the variance of tie-line is considered as risk term, which represents power fluctuations between the microgrid and the main grid. The tieline power fluctuation is modelled as covariance relationship between considered scenarios of wind, PV and interruptible loads. Eq (4) shows the expected profit of the microgrid.

$$E(P_{wind,t}, P_{pv,t}, P_{inr,t}, P_{chg,t}) = \lambda_t \Bigg(\sum_{w=1}^{N_w} P_{wind,w,t} + \sum_{s=1}^{N_s} P_{pv,s,t} - \sum_{j=1}^{N_d} P_{d,j,t} - \sum_{i=1}^{N_i} P_{inr,i,t} - \sum_{c=1}^{N_c}(P_{chg,c,t} - P_{chg,c,t-1}) \Bigg) - \lambda_{inr,t} \sum_{i=1}^{N_i} (P^{cap}_{inr,i,t} - P_{inr,i,t}) - \sum_{w=1}^{N_w} \lambda_{wind,w,t}(P^f_{wind,w,t} - P_{wind,w,t}) - \sum_{S=1}^{N_S} \lambda_{pv,s,t}(P^f_{pv,s,t} - P_{pv,s,t}) \quad (4)$$

The risk part of the proposed model is, the fluctuation in the tieline power(injected/drawal) to the maingrid from microgrid or vice-versa because of fluctuation in wind, PV and EV behavior residing in the microgrid. The following is modelled by taking the variance and covariance relations as given in eq (5).

$$V(P_{wind,t}, P_{pv,t}, P_{inr,t}, P_{chg,t}) = \sum_{t=1}^{T} \sqrt{P'_t HCOVH' P_t} \quad (5)$$

where,
E - Expected revenue of the proposed Microgrid EMS model
V - Variance in power fluctuation
λ_t - Forecasted price of electricity in the wholesale market
$P_{inr,t}$ - price of interruptible load
$\lambda_{wind,w,t}, \lambda_{pv,s,t}$ - Economic punishment for power curtailment of wind farm w and solar farm s respectively
$P_{wind,w,t}, P_{pv,s,t}$ - dispatched value of wind and solar power of wind farm w and solar farm s respectively
$P^f_{wind,w,t}, P^f_{pv,s,t}$ - forecasted wind power and solar power of wind farm w and solar farm s respectively (Input data)
$P_{d,j,t}$- critical load j at time t
$P^{cap}_{inr,i,t}$ - capacity of the interruptible load i at time instant t
$P_{chg,c,t}, P_{chg,c,t-1}$ - charging states of energy storage systems at time t and $t-1$ respectively
N_w, N_s, N_d, N_i and N_c - number of wind power stations, PV power stations, critical load, interruptible loads and BESS respectively resides inside the microgrid.
H - Diagonal Matrix containing uncertainty ratio of both wind and PV power plants
COV - covariance relation matrix.
$P^{'}_t$ - matrix has entries of dispatched power of wind and PV plants.
All price values are in $/kWh and all power figures are in kW. Eq (4) and eq (5) together with a risk aversion factor forms a risk assessment objective function for the microgrid EMS with an aim to minimize the operating cat as well as minimize the risk considering wind and PV uncertainty. The above proposed objective function is subjected to the following system constraints.

The first constraints is the tie-line power constraint given in eq (6) and eq (7) limits the power exchange between the microgrid and the utility grid. This constraint is important because excessive power exchange can lead to voltage instability and even blackouts.

$$P^{min}_{tieline} \leq \sum_{w=1}^{N_w}(1-\alpha_{w,t})P_{wind,w,t} + \sum_{s=1}^{N_s}(1-\alpha_{pv,t})P_{pv,s,t} - \sum_{j=1}^{N_d} P_{d,j,t} - \sum_{i=1}^{N_i} P_{inr,i,t} \quad (6)$$

$$\sum_{w=1}^{N_w}(1+\alpha_{w,t})P_{wind,w,t} + \sum_{s=1}^{N_s}(1+\alpha_{pv,t})P_{pv,s,t} - \sum_{c=1}^{N_c}(P_{chg,c,t} - P_{chg,c,t-1}) \leq P^{max}_{tieline} \quad (7)$$

The second constraint given in eq (8) and eq (9) are the energy storage constraint. The energy storage system is designed to store excess renewable energy during periods of low demand and discharge it during periods of high demand. However, the energy storage system has a limited capacity, which means that it must be operated within its charge/discharge rate and state of charge (SOC) constraints to ensure that it can meet the load demand when required.

$$-P_{chg,c}^{limit}\gamma_c \leq P_{chg,c,t} - P_{chg,c,t-1} \leq P_{chg,c}^{limit}\gamma_c \quad (8)$$

$$-P_{chg,c}^{limit}SOC_{min} \leq P_{chg,c,t} \leq P_{chg,c}^{limit}SOC_{max} \quad (9)$$

here, γ_c is the rate of charging/discharging of the energy storage system. $P_{chg,c}^{limit}$ is the maximum cap limit for charging/discharging.

The third constraint is the the interruptible load capacity constraint given in eq (10). Interruptible loads are those loads that can be temporarily curtailed or shed during periods of high demand. The capacity of the interruptible loads is limited, and the microgrid must ensure that they do not exceed their capacity during operation.

$$0 \leq P_{inr,i,t} \leq P_{inr,i,t}^{cap} \quad (10)$$

The forth constraint is the wind and solar power constraints given in eq (11) and eq (12) . These constraint ensures that the system operates within the limits of the available wind and solar power.

$$0 < P_{wind,w,t} < P_{wind,w,t}^{f} \quad (11)$$

$$0 < P_{pv,s,t} < P_{pv,s,t}^{f} \quad (12)$$

The fifth and last constraint given in eq (13) limits the maximum power flow through the distribution line to prevent overloading and damage to the equipment.

$$|P_{Tieline,t}| \leq P_{Tieline}^{max} \quad (13)$$

The above constraints ensures the safe and reliable operation of the microgrid EMS.

IV. Results

The above proposed mathematical model of microgrid EMS is built in MATLAB environment as a second order cone programming (SOCP). We have used commercially available 'coneprog' function which solves the proposed (SOCP) problems using an interior-point algorithm [13]–[15]. The input data related to the microgrid EMS optimization model is given in the table

A. Considered Input data

The proposed risk model is analyzed in a modified IEEE 14 bus as shown in fig 2 below. The system has 2 WTs are considered at bus 2 and bus 3 respectively; 2 BESS are considered at on buses 6 and 8; two PVs are considered at buses 4 and 5. In terms of demand side management, 3 interruptible loads located on buses 12,13 and 14. Rest all loads are considered as critical (non-Interruptible) load. The

TABLE I
Input Parameters

Parameters	Value
Economic punishment for wind curtailment(Rs/kW)	1.5,1.7
capacity of WT1 and WT2 (kW)	100, 200
Economic punishment for PV curtailment(Rs/kW)	0.6,0.7
Capacity of PV1 and PV2 (KW)	30,25
Curtailment Price of Interruptible loads [IL1;IL2;IL3] (Rs/KWh)	1,1.1,1.2
Capacity of IL1;IL2;IL3 (KW)	10,15,20
Capacity limits of BESS1 and BESS2 (KWh)	20;30
Charge/Discharge limit of BESS (A/Ah)	0.8,0.2
SOC limits of BESS (%)	40,90

forecasted generation data from the Considered solar power plants and wind power plants with forecasted are shown in fig 3 and fig 4. ARIMA model is used to generate the scenarios from the forecasted output of PV and wind turbines.

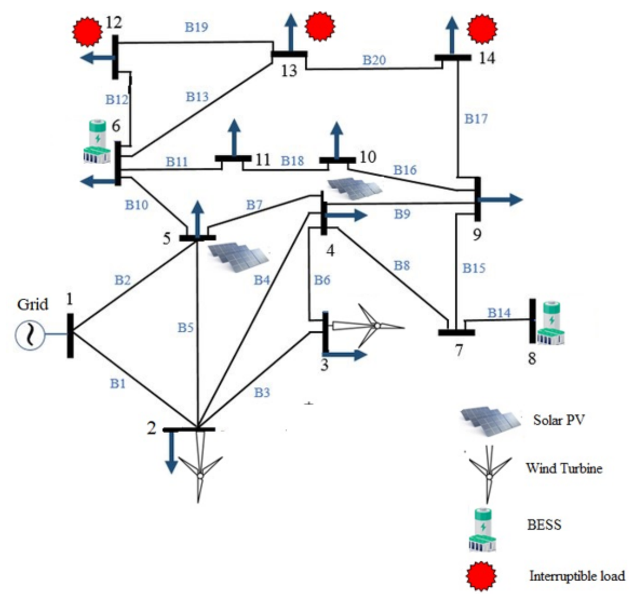

Fig. 2. Modified IEEE 14 Bus system

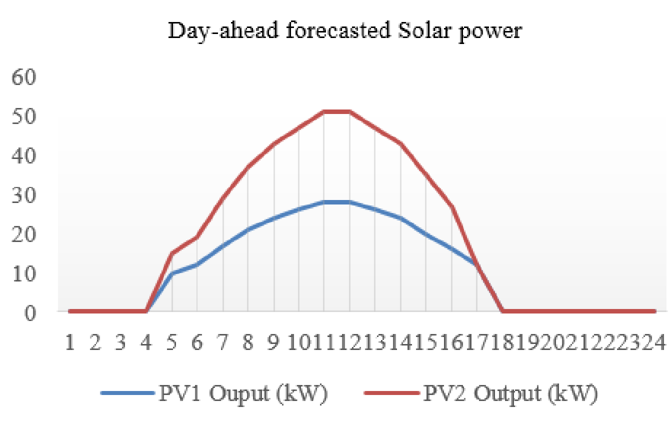

Fig. 3. Forecasted solar power generation profiles

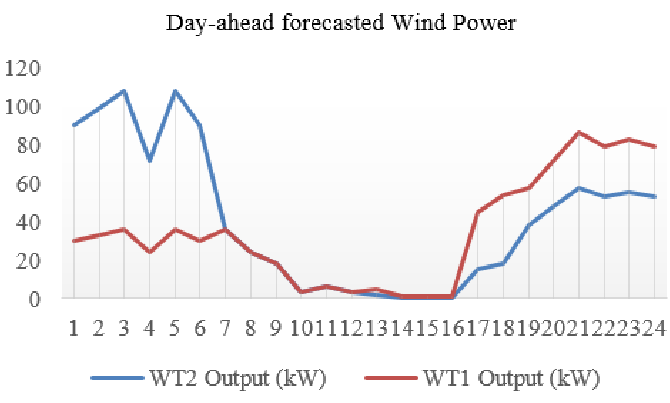

Fig. 4. Forecasted wind power generation profiles

The forecasted day ahead market price used for the revenue calculation and the microgrid forecasted day ahead load is plotted in the fig 5 and fig 6 below.

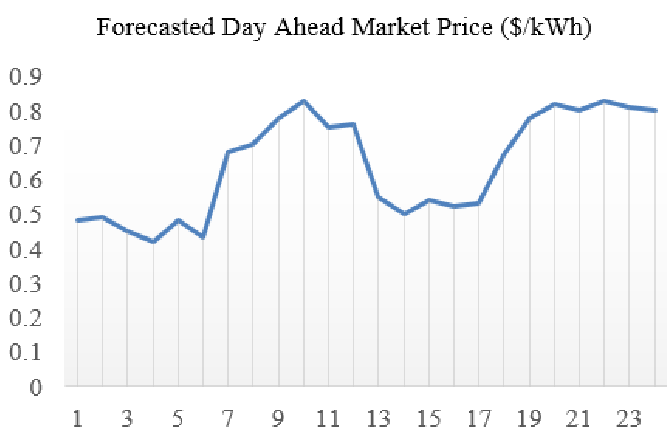

Fig. 5. Forecasted Day Ahead Market Price Curve

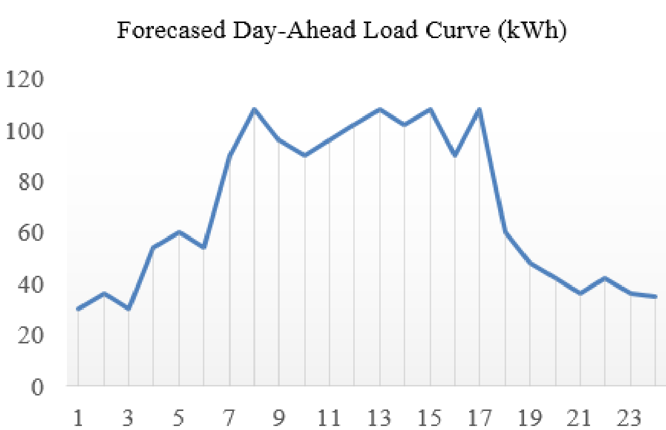

Fig. 6. Forecasted Day Ahead Load curve

B. Results

The microgrid-EMS use these data to plan and schedule energy production and consumption, ensuring a reliable and cost-effective operation of the microgrid at the same time managing the risk of fluctuation in the tie line connection to the main grid. The time horizon considered is 24 hours with a time period of 1 hour. The forecasted generation, load and market price data are given as inputs to the developed optimization model in Section III.

a) Demand Side Management: Of all the loads, three loads are considered as interruptible loads for optimal demand side management. IL1, IL2 and IL3 are the interruptible loads (ILs) considered. When the generation is less than the load demand and electricity price is higher than the expense of shedding load, these ILs shows willingness to curtail their load to the allowable capacity for revenue generation of the microgrid. The analysis of the microgrid system revealed that there is a peak load in the system from 10-16 hours. During this period, the generation is primarily from solar power. The wind power generation is relatively low. To cope up with the generation and stabilize the system, it was observed that interruptible loads were shed down during this period based on the incentive factor $\lambda_{inr,t}$ used in eq (4). This shed is an effective way of balancing the generation and load demands in the microgrid system as shwon in fig 7.

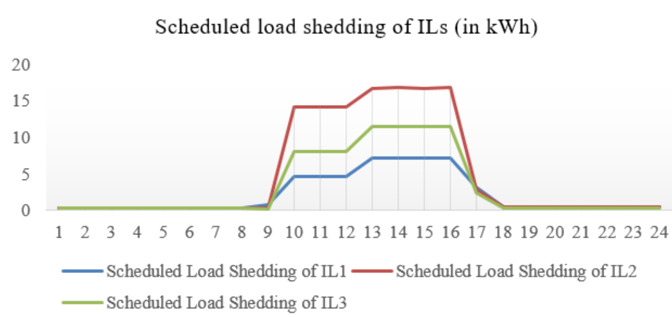

Fig. 7. Scheduled load shedding of ILs (in kWh)

b) Tieline Power: The tie-line power obtained in plotted in fig 8 below. Based on the results obtained, it can be observed that during the hours of (1-6hrs) and (16-24hrs), the tieline power to the main grid is high, as the power generation from the wind farms is greater than the load. This excess power is sold to the main grid through the tieline. On the other hand, during the hours of (6-16hrs), the power generation in the system is mainly from solar sources, and the energy storage units act as a power source to meet the peak load demand. However, for some peak hours, when the generation in the system is lesser than the load, power is purchased from the main grid through the Tie line (the negative values). The tie-line power fluctuation maximum limit is considered as 80kW for this study.

V. Conclusions

In conclusion, the results of the study demonstrated here shows the effectiveness and importance of risk manage-

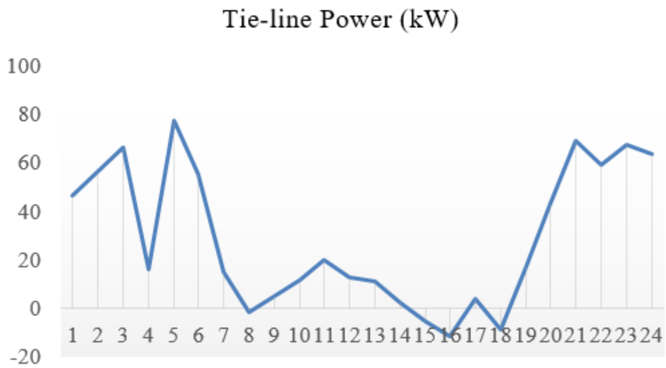

Fig. 8. Variation of Tie-Line Power

ment study in optimizing the energy management of a grid-connected microgrid. By analyzing the wind and solar power generation curves, we were able to develop an optimal day-ahead operating schedule for the microgrid, taking into account the variability in renewable energy availability. Load shedding during peak periods was observed to stabilize the system, and the tieline power was effectively used to balance the energy supply and demand. The study highlights the potential benefits of adopting a proper approach for robust and risk-aware optimization of grid-connected microgrid energy management. The findings of this study have provided valuable insights into the operation and management of grid-connected microgrid using a robust and risk-aware mean-variance optimization approach.

References

[1] E. G. Vera, C. A. Cañizares, M. Pirnia, T. P. Guedes and J. D. M. Trujillo, "Two-Stage Stochastic Optimization Model for Multi-Microgrid Planning," in IEEE Transactions on Smart Grid, vol. 14, no. 3, pp. 1723-1735, May 2023, doi: 10.1109/TSG.2022.3211449.

[2] Zhao H, Lu H, Li B, Wang X, Zhang S, Wang Y. Stochastic Optimization of Microgrid Participating Day-Ahead Market Operation Strategy with Consideration of Energy Storage System and Demand Response. Energies. 2020; 13(5):1255. https://doi.org/10.3390/en13051255

[3] S. Pandey et al., "Robust Optimization Methodology for Generation Sizing of a Microgrid," 2021 IEEE Power & Energy Society General Meeting (PESGM), Washington, DC, USA, 2021, pp. 01-05, doi: 0.1109/PESGM46819.2021.9637851.

[4] AlDavood MS, Mehbodniya A, Webber JL, Ensaf M, Azimian M. Robust Optimization-Based Optimal Operation of Islanded Microgrid Considering Demand Response. Sustainability. 2022; 14(21):14194. https://doi.org/10.3390/su142114194

[5] Rohit Trivedi, Shafi Khadem,Implementation of artificial intelligence techniques in microgrid control environment: Current progress and future scopes, Energy and AI, Volume 8,2022,100147,ISSN 2666-5468,https://doi.org/10.1016/j.egyai.2022.100147.

[6] Mosavi A, Salimi M, Faizollahzadeh Ardabili S, Rabczuk T, Shamshirb and S, Varkonyi-Koczy AR. State of the Art of Machine Learning Models in Energy Systems, a Systematic Review. Energies. 2019; 12(7):1301. https://doi.org/10.3390/en12071301

[7] Sang J, Sun H, Kou L. Deep Reinforcement Learning Microgrid Optimization Strategy Considering Priority Flexible Demand Side. Sensors. 2022; 22(6):2256.

[8] B. Harish, D. Panda, K. R. Konda and A. Soni, "A Comparative Study of Forecasting Problems on Electrical Load Timeseries Data using Deep Learning Techniques," 2023 IEEE/IAS 59th Industrial and Commercial Power Systems Technical Conference (I& CPS), Las Vegas, NV, USA, 2023, pp. 1-5, doi: 10.1109/ICPS57144.2023.10142125.

[9] Panda, D., Singh, S.N. Optimal Portfolio Selection of GenCo Under Congestion Risk in Multimarket Environment. Technol Econ Smart Grids Sustain Energy 2, 12 (2017). https://doi.org/10.1007/s40866-017-0029-2.

[10] Panda, Debasmita & Singh, S N & Kumar, Vimal. (2014). Risk constraint profit maximization in a multi-electricity market. IEEE Power and Energy Society General Meeting. 2014. 10.1109/PESGM.2014.6939300.

[11] Y. Lin, J. Zhang, Q. Ying, Y. Li, J. Liu and J. Zhou, "Scenarios Analysis Method Based on Wind and Photovoltaic Power Output Correlation," 2021 IEEE Sustainable Power and Energy Conference (iSPEC), Nanjing, China, 2021, pp. 19-24, doi: 10.1109/iSPEC53008.2021.9736124.

[12] Martin Densing, Yi Wan,Low-dimensional scenario generation method of solar and wind availability for representative days in energy modeling, Applied Energy, Volume 306, Part B,2022,118075,ISSN 0306-2619.

[13] L. Bai, Q. Hu, F. Li, Tao Ding and H. Sun, "Robust mean-variance optimization model for grid-connected microgrids," 2015 IEEE Power & Energy Society General Meeting, Denver, CO, 2015, pp. 1-5, doi: 10.1109/PESGM.2015.7286489.

[14] Martin Legry, Frédéric Colas, Christophe Saudemont, Jean-Yves Dieulot, Olivier Ducarme. Mixed integer quadratic programming receding horizon microgrid supervisor. 2019 IEEE Milan PowerTech, Jun 2019, Milan, Italy.

[15] Nguyen-Duc T, Hoang-Tuan L, Ta-Xuan H, Do-Van L, Takano H. A Mixed-Integer Programming Approach for Unit Commitment in Micro-Grid with Incentive-Based Demand Response and Battery Energy Storage System. Energies. 2022; 15(19):7192. https://doi.org/10.3390/en15197192.