Modified Flower Pollination Algorithm for Energy Forecasting and Demand Management coupled with Improved Battery Life for Smart Building Micro-grid

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***Abstract*—This paper presents the Modified Flower Pollination Algorithm-based Multi-Layer Perceptron Neural Network (MFPA-MLPNN) as an optimization technique for efficient power flow management in a Smart Building Microgrid (SBMG) integrated with solar and wind generation, and Electric Vehicle Batteries (EVBs) within grid connected structure while concurrently reducing optimization processing time. To achieve both technical and economic superiority, two optimization objectives are addressed. Firstly, a Demand Response (DR) framework is harnessed to accommodate the stochastic behavior and forecasting errors associated with intermittent sources. Secondly, the degradation of EVBs is considered, ensuring an economically viable power flow proposed strategy for both EV owners and microgrid (MG) authorities. Power generation of Variable Renewable Energy Sources (VRES) has been forecasted using MLPNN. Battery degradation and system stability under the action of the proposed topology have been evaluated using a simulation-based environment. Results show a significant decrease in battery degradation and processing time using the proposed MFPA-MLPNN optimization architecture.**

***Index Terms*—Smart Building Microgrid, Renewable energy, Electric vehicle batteries, Energy management, Demand response, Flower pollination algorithm.**

I. Introduction

The energy consumption in buildings contributes to 40% of global energy requirements, driving a need towards sustainable solutions to address climate concerns. Transformation in energy and environmental-centered solutions is thus evident from transitioning to low-carbon technologies and smart cities [1], especially in developed nations. This shift involves a significant share of Variable Renewable Energy Sources (VRES) and widespread Electric Vehicle (EV) adoption [2].

Solar and wind power exhibit a stochastic character attributed to the variability of their uncertain and unpredictable parameters, causing fluctuations over time. Thus, it is important to study the atmospheric viability of solar and wind energy systems when examining economic as well as technical factors for Smart Building Micro Grid (SBMG).

The existing literature on microgrid energy management solutions primarily focuses on small buildings, often neglecting uncertainties associated with various energy sources (such as solar irradiance, wind speed, and vehicle travel plans) due to processing time and complexity constraints in the optimization process. Authors in [3] developed an energy management system (EMS) for zero-energy building as a mix of Neural Network and Model Predictive Control (NNPC). The building is powered with a 1.75 kW hybrid system which includes 750 W of low-speed wind turbines and a 1 KW photovoltaic (PV) unit, and alongside, two 100 Ah storage batteries. The NNPC however suffers from computational complexity and risk of overfitting. A hybrid approach integrating artificial neural network (ANN) and bacterial foraging optimization algorithm (BFOA) is presented in [4] to manage MG system that contains wind turbine, PV system, and storage batteries. An intelligent EMS strategy based on a Recurrent Neural Network (RNN) and Ant-Lion Optimizer (ALO) algorithm is described in [5] to identify energy scheduling in MG. The BFOA and ALO face challenges such as limited exploration in high-dimensional spaces and sensitivity to parameter tuning, impacting their convergence and overall performance. Developing optimization and ANN approaches are greatly useful for small-scale MG that rely only on renewable energy sources and high-capacity batteries for storage. Unlike existing models addressing MG energy management, such as [6], the proposed SBMG's model formulation is intricate due to the inclusion of commercial electric vehicle and residential charging demands. Despite extensive research optimizing power flow using in-system batteries and studying battery health under fast charging/discharging, there is a notable gap in enhancing battery life under Vehicle-to-grid (V2G) or G2V operations. In this work, EVs are employed as on-demand backup power sources, strategically utilized during peak load hours within the microgrid. This research primarily focuses on improving battery life in V2G and G2V operations while ensuring network stability and efficient utilization of connected sources. The main objectives are as follows:

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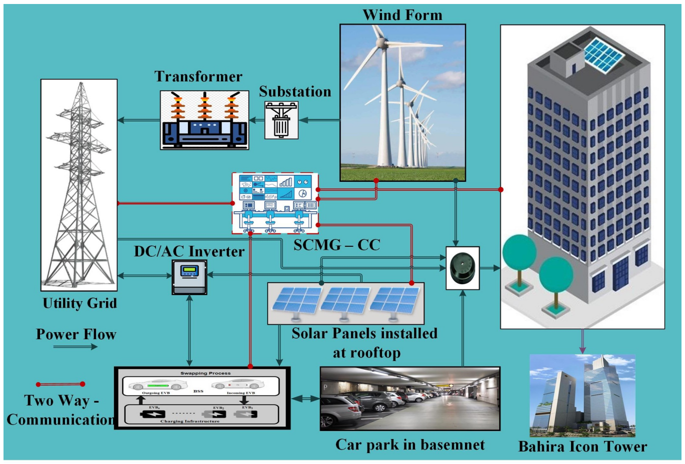

Fig. 1: Smart building microgrid integrated with EVs.

II. SBMG Energy Management Model

This section aims to create a mathematical model, as depicted in the detailed flowchart Fig. 3, which considers fluctuating VREs, EVBs, and building electric demand. Each time slot factors the variable household and VRE output, unknown electricity cost, and State of Charge (SoC) for incoming EVBs. In this section, EVBs and VREs mathematical modeling, Demand forecast model, Demand response, and problem formulation are described.

A. Network modelling

*1) **EVBs mathematical modelling**:* The building is assumed to have 300 residential EVs on the usual day and an extra 80 EVs parked in the basements for visitors. Within the building parking facility, Electric Vehicle Charging Booths (EVCBs) are strategically placed to recharge EVs during off-peak hours, capitalizing on the lowest electricity rates. Subsequently, surplus electricity is supplied to grid authorities at higher tariffs during peak hours. It is noteworthy that the number of EVs connected to MG fluctuates based on the routines of individual customers. The EV battery behavior could be expressed as, e.g.[7]:

$$y_i\,(t+1) \,=\, x_i\, y_i(t) \,+\, z_i\, w_i(t) \tag{1}$$

where k is time index, i is a variable index presenting EV owner i^{th} ={1, …, N}. y_i is i^{th} battery SoC while x_i shows dissipation factor. The $z_i = \left[\eta^c_{i,}\, \eta^d_i\right]$ is charging/discharging coefficient vector and w_i is the power vector defined as $w_i(t) = \left[w^c_i(t)\, w^d_i(t)\right]^T$ with w^c_i and w^d_i showing charging and discharging powers, respectively.

To anticipate the impact of widespread EVB adoption on the electric demand landscape, a stochastic model is devised to monitor the unpredictable charging and discharging behavior of EV users. This model considers variables like arrival/departure times, and daily mileage as random variables due to their uncertain nature. This addresses the uncertainty associated with EV charging operations aiding to effective charging management. Eq.(2) and Eq.(3) representing departure and arrival times [8], respectively, are integral to this stochastic approach.

$$f(x \mid \psi, \zeta, \eta) = \frac{\zeta\left(\frac{\kappa+1}{2}\right)}{\delta\sqrt{\kappa\pi}\zeta\left(\frac{\kappa}{2}\right)}\left[\frac{\kappa+\left(\frac{x-\psi}{\delta}\right)^2}{\kappa}\right]^{-\left(\frac{\kappa+1}{2}\right)} \tag{2}$$

$f(x \mid \psi, \zeta, \eta)$ is the distribution parameter. Location scale values are as follows: $\psi = 8.08$, $\zeta = 1.08$, $\eta = 2.10$ and variance $\kappa = 3.92$.

$$f(x \mid \psi, \delta) = \frac{1}{\delta\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\psi}{\delta}\right)^2} \tag{3}$$

Distribution parameters are selected as a normal distribution with ψ and δ with their values of 16.4 and 2.76 respectively. EV charging and discharging are approximated by using departure and arrival time profiles.

To address high costs and capacity reduction in batteries for short duration, real-life aging tests for Capacity Etiolation (CE) are impractical due to expense and time constraints [9]. Artificial Neural Networks (ANNs) emerge as a viable solution for predicting battery lifetime. CE is influenced by temperature, voltage, current, and SoC [9], incorporating Depth of Discharge (DoD) and average SoC in calculations. Battery capacity is determined at specific temperature T and voltage V, with charge throughput Q measured in ampere-hours and time t in days. Authors in [10], [11] suggest both linear and square root aging for overcharge throughput Q. In idle mode, SoC and temperature significantly impact capacity and thus for precise CE estimation, real-time data from NASA Ames Prognostics Data Repository [12] is utilized. The dataset contains battery currents, voltages, temperature, and corresponding SoC at different ambient temperatures, and serves as an ideal resource for training the ANN to predict battery CE dynamics. The neural network architecture depicted in Fig. 3 is employed for battery CE prediction.

*2) **VRES mathematical modelling**:* The VRES consists of solar and wind energy sources, with consideration of zero marginal cost to maximize the clean power utilization given as:

$$P_{\mathrm{R}}(t) = P_{\mathrm{PV}}\,(t) + P_{\text{wind}}\,(t) \tag{4}$$

where $P_{\mathrm{PV}}\,(t)$ and $P_{\text{wind}}\,(t)$ denote the solar and wind energy at a given time instant t, respectively. Available solar energy has been evaluated by using solar irradiation data of Karachi which is sourced from the World Bank Group [13]. On the other hand, the total available wind energy in Karachi is evaluated using the wind power potential from [14]. The VRES output power on an hourly basis is shown in Figs. 4 and 5, respectively. To introduce forecasting of available renewable power, a neural network is trained with inputs (wind speed, temperature, and irradiance) and targets (wind and solar power). The use of a prediction framework for VRES generation ensures the capability of the proposed architecture to be installed at any realistic scenario-optimization using predicted information. The neural network architecture given in Fig. 3 is used for the prediction of VRES power generation.

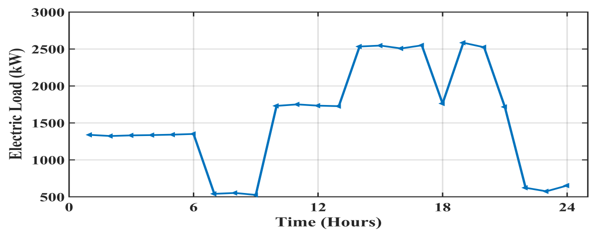

Fig. 2: Electric load of SBMG (hourly basis)

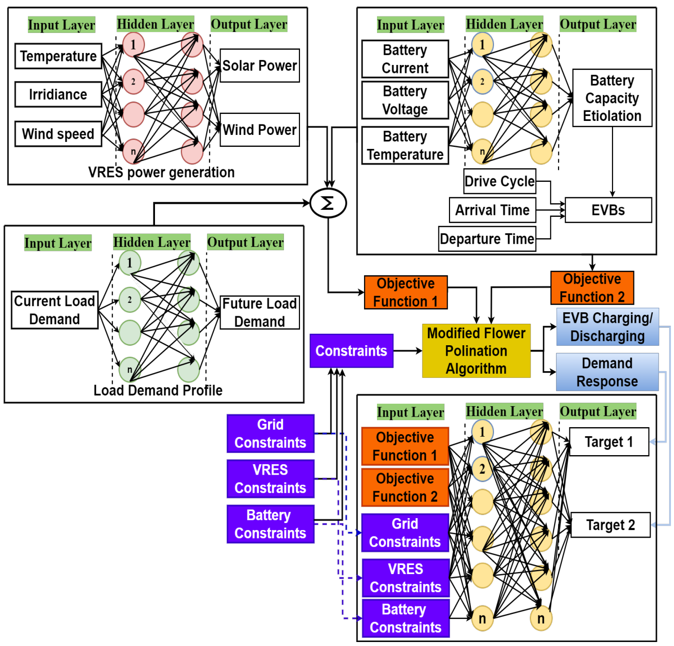

Fig. 3: Flowchart Diagram of proposed MFPA-MLPNN architecture

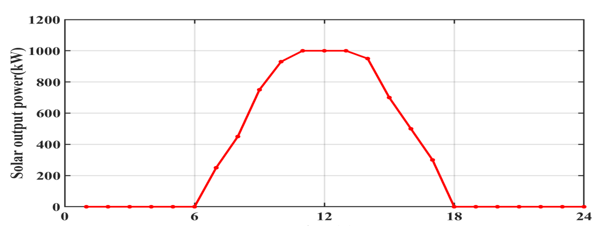

Fig. 4: Output power of Solar (hourly basis)

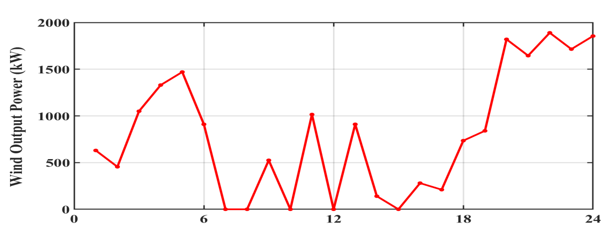

Fig. 5: Wind output power (hourly basis)

*3) **Demand forecast model**:* The primary goal of demand forecasting is to enhance cost efficiency, ensuring that the total power demand for the entire building, illustrated in Fig. 2, stays below a specified threshold. This allows for an even distribution of loads throughout the day. Future demand forecasting employs a neural network with current load demand as input and future demand as the target, depicted in Fig. 3.

*4) **Demand response**:* The energy management system prioritizes minimizing power consumption during peak hours by shifting non-critical loads to off-peak periods. Smart meters monitor utility demand limits, and the control room ensures critical loads remain unaffected. Load-shifting decisions are based on priority levels, reflecting consumer preferences and promoting flexibility. This system enhances reliability, flexibility, and cost-effectiveness in electricity usage, optimizing overall efficiency. The control room's demand response signal guides the power consumption of controllable non-critical loads, contributing thus to efficient energy management.

*5) **Problem formulation**:* The problem involves simultaneously minimizing two computing objective functions: overall hourly load demand and batteries CE, while adhering to various equality and inequality constraints. The overall load demand comprises a fixed load throughout the day and a variable load allowed only during off-peak hours, as expressed in (5).

$$P_L = \sum_{t=1}^{24} P_F(t) + \sum_{t=1}^{18} P_V(t) + \sum_{t=19}^{21} P_V(t) + \sum_{t=22}^{24} P_V(t) \tag{5}$$

$$\text{minimize} \sum_{t=1}^{24} P_L(t) = P_L \tag{6}$$

where: P_L is the overall load demand of the building in kWh. P_F is the fixed electric load with continuous operation 24/7 in kWh. P_V is the variable electric load having variable off-peak hours operation in kWh. t is the time interval in h. Minimize the objective function, representing the overall load demand, while adhering to the constraint that the total generation must equal the sum of power generated by solar and wind sources. (7) shows the total generation ($P_{\mathrm{G}}(t)$) at time t and the inequality constraint based on the generators' power limits.

$$P_{\mathrm{G}}(t) = P_{\mathrm{PV}}(t) + P_{\mathrm{wind}}(t) \ \ \textbf{\&} \ \ P_G^{\min} \leq P_G(t) \leq P_G^{\max} \tag{7}$$

where $P_G^{\min}$ and $P_G^{\max}$ are min and max values of real powers allowed from the generators, respectively. However, for comparison purposes, the total CE of an EV battery can be minimized by taking the sum of all day capacity loss due to charging and discharging as:

$$\text{minimize} \sum_{t=1}^{24} C_e(t) \tag{8}$$

The proposed battery CE model adheres to planning and operation constraints, applied to each time interval within the optimization time horizon. It ensures that the charging and discharging power of an EV stays within the specified minimum and maximum limits at each time interval, as outlined in (9).

$$P_c^{\min} \leq P_c(t) \leq P_c^{\max} \ \ \textbf{\&} \ \ P_d^{\min} \leq P_d(t) \leq P_d^{\max} \tag{9}$$

where $P_c^{\min}$ and $P_c^{\max}$ are the minimum and maximum limits of charging powers for the EV battery, respectively. $P_d^{\min}$

and $P_d^{\max}$ are the minimum and maximum discharging power limits, respectively. The V2G discharging power, $P_{V2G}(t)$, is equal to the sum of powers from all EVs available at parking ($P_{V2G}(t) = N_{Av} * P_d$). Where N_{Av} is the number of parked EVs available for discharging towards the grid and have SoC more than $SoC^{\min}$.

The total power available at the supply side should be greater than the required power at the demand side of SBMG, as a constraint ($P_L(t) \leq P_R + P_{V2G}$). The EV batteries should charge and discharge to minimize battery CE following the constraints given below:

$$SoC^{\min} \leq SoC(t) \leq SoC^{\max} \text{ \& } DoD(t) = 100\% - SoC(t) \tag{10}$$

$$T^{\min} \leq T(t) \leq T^{\max} \text{ \& } V_d \leq V(t) \leq V_c \tag{11}$$

where $SoC^{\min}$ and $SoC^{\max}$ are the minimum and maximum limits of EV battery SoC, respectively. $DoD(t)$ and $SoC(t)$ represent Depth of Discharge (DoD) and SoC at each time instant, respectively. $T^{\min}$ and $T^{\max}$ are the minimum and maximum limits of cell temperature for the EV battery, respectively. Voltage limits are V_d for discharging and V_c for charging.

B. *Control algorithm*

1) Modified flower pollination algorithm based on multi-layer perceptron neural network (MFPA-MLPNN): Yang et. al. created the Flower Pollination Algorithm (FPA) [15]. It has been used in this paper to optimize the power flow for demand-side load management and to keep the process economical by decreasing the battery degradation process. The worldwide pollination and flower constancy [16] can be depicted using (12)–(14)

$$y_n^{t+1} = y_n^t + \alpha \mathbb{L}(\omega) \left(x_* - y_n^t \right) \tag{12}$$

$$\mathbb{L} \approx \frac{\omega \tau(\omega) \sin(\pi\omega/2)}{\pi} \left(\frac{1}{\beta^{1+\omega}} \right) (\beta >> \beta_0 > 0) \tag{13}$$

$$y_n^{t+1} = y_n^t + \varepsilon \left(y_i^t - y_k^t \right) \tag{14}$$

$L(\lambda)$ is the Lévy flight-based step size, which corresponds to the pollination's strength. $\tau(\omega)$ is the standard gamma function, and the distribution is suitable for large steps $\beta > 0$. where y_i^t and y_k^t are pollen from separate flowers of the same plant species, imitating flower consistency in a small area. As y_i^t and y_k^t are from the same species in a local random walk, the ε is sampled from uniform distribution over the interval [0, 1].

The computational time challenge in global pollination is mitigated by employing a modified flower pollination algorithm based on a multi-layer perceptron neural network (MLPNN) architecture. Thus, neural networks are used to establish input-output relations for system dynamic understanding. The energy management architecture for SBMG's multiple objectives is simulated using MFPA in MATLAB, addressing equality and inequality constraints. The objective function given below:

$$\text{Minimize } F = \sum_{t=1}^{24} [P_L(t), C_e(t)] \tag{15}$$

TABLE I: **Parameters and values**

Symbol	Value
VRES Useful Life (n)	25
Total capacity of wind farm (C_w)	2300kW
Capacity Factor ($C_p(w)$)	40%
Total capacity of solar plant (C_{pv})	800kW
Capacity Factor ($C_p(pv)$)	30%
Daily EV resident and visitor park batteries ($V_{1,2}$)	300, 80
Charging and Discharging Coefficient of batteries of EVs (z_i)	0.1
Max capacity of batteries of EVs ($Z^{\max}$)	85KWh
Max and Min SoC of batteries of EVs (Y_H). (Y_L)	70kWh, 10kWh
Max charging and discharging power of EV's batteries (W_H), (W_L)	60kW, 60kW
Dissipation factor of Batteries (x_i)	1

The objective functions of MFPA capturing the relationship between load demand, CE, and input variables, are used as input-output data for training the MLPNN controller. Various scenarios are simulated to collect data for training, validation, and testing sets. The MLPNN is trained using the same inputs as MFPA as $y(t) = f(x(1), x(2), x(3), \ldots x(n))$, where, $x(1), x(2), x(3), \ldots x(n)$ are input states of MLPNN controller and $y(t)$ presents output states (targets). The optimization problem involves minimizing a combined objective function, F, comprising load demand (P_L) and CE for each time slot. MLPNN is employed to estimate day-ahead load demand and CE using input data such as wind and solar output power, estimated charging/discharging, temperature, voltage, and current of EV batteries. The regression model, informed by training data, is used to derive predictions, with a learning algorithm optimizing the model during training. The MFPA data is divided for training (75%) and validation (25%).

III. Simulation and Results

A comparative investigation is performed in MATLAB to demonstrate the efficacy of the proposed power flow management in handling network overloading during peak hours. The operational parameters for VRES are given in Table. I. The *Tesla Model S* [17] is selected for the modeling process and it has a battery of 85 kWh capacity. The acceptable SoC values for minimum discharge and maximum charging are considered to be 10 and 80 $\%$ respectively.

The MFPA iteration for time instant optimization averages 120 seconds, making it impractical for real-time applications. In contrast, the MLPNN takes less than 5 seconds on average to solve the multi-objective function. The trained MLPNN demonstrates significantly shorter simulation times compared to implementing MFPA for power flow management in the proposed SBMG architecture as shown in the comparative analysis in Fig (6).

Results in Fig. (7) compare optimized and original power consumption and the maximum limits. The actual power demand surpasses the allowable limit, resulting in network load issues, subsequent overloading, and eventual network failure. The proposed optimization algorithm effectively suppresses the network electric demand from the grid below the allowed range by leveraging the capabilities of in-system EVBs. The total generated output power from wind and solar are shown

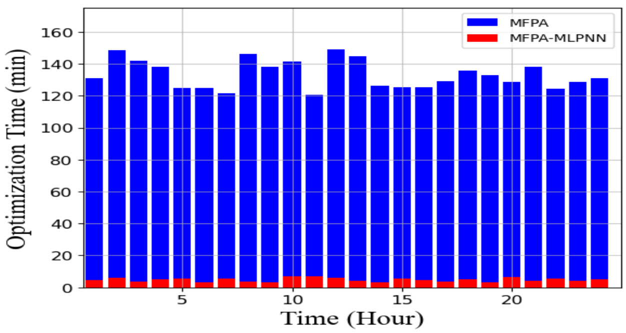

Fig. 6: Comparative analysis of optimization time

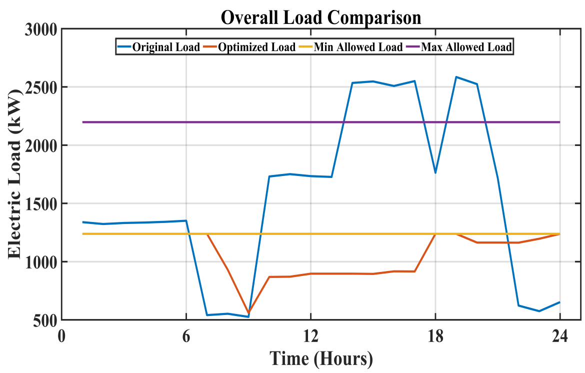

Fig. 7: Comparison of overall load demand: optimized versus original

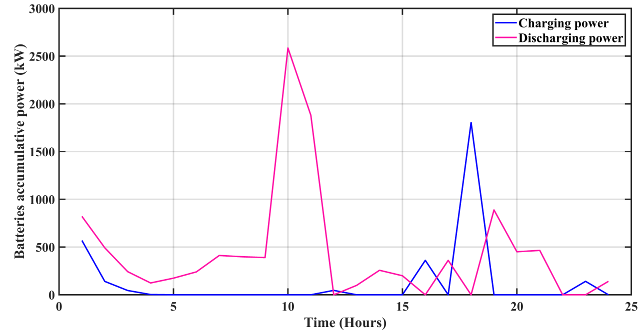

Fig. 9: All regular EVs whose batteries are charging/discharging at the building on a typical day

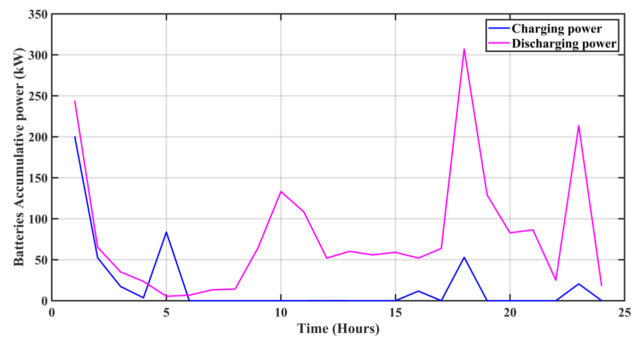

Fig. 10: All irregular EVs whose batteries are charging/discharging at the building on a typical day

in Fig. (8). Noteworthy, wind and solar capacities are selected following the observed load demand of the SBMG. Fig. (9) depicts optimized residential EV charging and discharging in the building within the SBMG network, based on estimated EV availability from departure and arrival times. Before MFPA-MLPNN optimization, linear battery charging led to network overloading. Post-optimization, EVBs dynamically pull power during off-peak hours, reducing the grid load. Notably, this approach contributes to network overload control and ensures sufficient charging for EVB functionality. Similarly, external EV visitors adhere to curtailment limits, as shown in Fig.(10), ensuring overall charging within constraints through two-way communication links. This enables EVBs to be effectively utilized for network overload management even after disconnecting from SBMG, optimizing power consumption and risks associated with network failure.

The result in Fig.(11) illustrates the battery capacity throughout its life cycle without V2G participation and with optimized controller-enabled V2G. The naturally decreasing graph lines depict capacity degradation. This etiolation estimated using manufacturer-provided base values aligns with a linear decrease as observed from the manufacturer's data. As depicted in Fig. 11, the battery takes 1270 cycles without MFPA-MLPNN and 2701 cycles with MFPA-MLPNN to reach their respective critical states. The proposed optimizer extends the life cycles of participating batteries, aligning to maximize

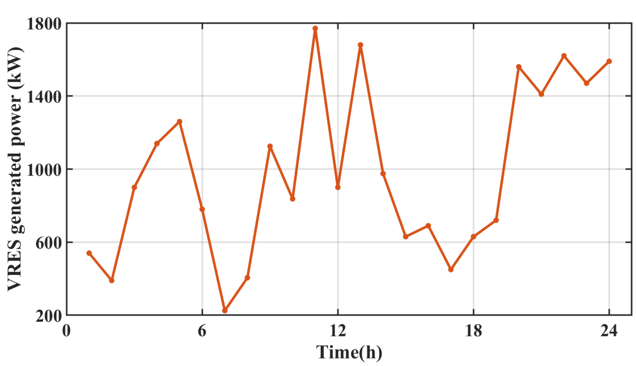

Fig. 8: Total power generated from VRES

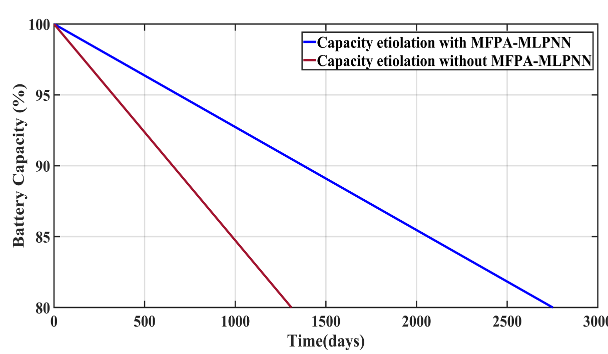

Fig. 11: Battery Capacity degradation over life

battery health. This increase in battery life reduces the V2G penalties to the Microgrid (MG) and the EV owners. The results shows a significant improvement in battery life in V2G and G2V operations, ensuring network power flow stability and efficient utilization of connected resources.

IV. CONCLUSION

In this paper, the role of EVBs has been highlighted in optimizing SBMG power flow management specifically addressing the intermittent behavior of VRES. The proposed MFPA-MLPNN has demonstrated its efficacy through comprehensive testing that incorporated the stochastic nature of both VRES and EV driving cycles, including arrival and driving patterns. The network demand stress on the utility grid is adeptly diminished by the proposed control algorithm, which dynamically regulates the connected flexible loads and manages the charging and discharging of EVBs. With optimized operation, electric demand stays below the allowed maximum network power flow capacity. Additionally, this proposed controller significantly reduces EVB degradation resulting from V2G and G2V operations by controlled charging/discharging cycles, adeptly managing the EVB degradation process and minimizing it to the utmost extent, adding a significant increase in the battery life cycle. Integrating EVBs into the microgrid eliminates the need for grid expansion, reducing overall electricity costs significantly. Future work would aim at detailed techno-economic analysis to demonstrate the effectiveness of the proposed optimized model and its impact on the overall cost-effectiveness of the grid system.

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