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Economic operation based sizing of hybrid Microgrid considering Battery Energy Storage System

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Abstract: The microgrid is described as a localized low-voltage power distribution system integrating DG units and ESS to supply electricity to some small or remote communities. In this respect, the ESS stores energy when demand is low and releases the stored energy during peak hours. Real-time power balancing remains a major issue for isolated micro-grids using intermittent renewable DG sources. Battery Energy Storage Systems (BESS) can solve the problem as they can offer reserve capacity to meet the load changes. However, battery degradation significantly affects the BESS lifetime performance because degradation depends upon the cumulative energy throughput which has units in terms of kilowatt-hours (kWh) or megawatt-hours (MWh). When there is degradation affecting capacity reduction, there is a direct impact on the energy delivered to the load, and therefore it must be considered in system optimization. To reduce the operation costs and to make the electricity prices affordable for the consumers, the degradation effects must be included while optimizing the microgrid operation. For this, more detailed simulation on an hourly basis of battery discharge profile needs to be performed so as to assess the degradation effects based on actual discharge patterns. Then degradation costs and life estimations are included in the optimization. It is observed that higher average kWh and actual MWh throughput parameters increase operation costs in general while lower the electricity cost for the end user. This study presents an optimization method for minimizing microgrid operating costs and customer electricity expenses over the 24-hour period under consideration, with explicit modeling of BESS degradation. Accelerated Particle Swarm Optimization (APSO), the Modified Jaya (M-JAYA) algorithm, and the Linear Programming Interior-Point (LP-IP) method are implemented to optimize parameters related to degradation. Comparative results showcase the ability of these algorithms with respect to BESS lifetime, degradation cost, system operating cost, and customer electricity cost.

KEYWORKS: Battery Energy Storage Systems (BESS), Microgrid, Distributed Generations, Throughputs, Degradation effect, optimization.

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Introduction

Microgrids integrating Distributed Energy Resources (DERs) are increasingly recognized as future smart grid system implementations of the new age. Microgrids, by being equipped with renewable DG units and ESS, pump power to local as well as remote communities while simultaneously improving the resilience of the entire system. But the intermittent generation of renewable DG is often not synchronized with load demand fluctuations, which results in fluctuations in voltage and frequency. These fluctuations, however, can be regulated through the export and import of energy using ESS by storing energy at times of low load demand and discharging it at times of high demands, thus, ensuring reliable and stable power supply. While many ESS technologies are present, Battery Energy Storage Systems (BESS) have attracted considerable interest due to their immense energy/power density levels, scalability, and potential for applications such as peak shaving, renewable integration, and load levelling within Microgrids [1]. For grid-connected applications, Lithium-ion batteries are broadly used, mainly because of their high energy density, longer cycle life, and ability to operate at high depths of discharge (DoD). The performance of a BESS depends highly on its lifetime and discharge rate, which directly affect energy efficiency and system economics [2], [3].

Until the settings are optimized to offer uninterrupted power supply, Microgrids need operation in a manner that takes both operational and electricity costs into consideration. This staircase requires proper determination of BESS sizing and aging consideration over time. Battery degradation, mainly caused by energy throughput and cycling of discharging and charging cycles, is the most vital factor affecting both lifetime and capital cost of the storage system [4]. However, while there are many studies on cost minimization of microgrid systems using BESS, most of them neglect degradation consideration or consider it in a very simplified capacity-based approach [5]. More recently, microgrid operation and battery sizing have been addressed by many different optimization approaches, including In [6], a Mesh Adaptive Direct Search (MADS) algorithm was employed to identify the optimal operating strategy of a microgrid, focusing on operating cost minimization while satisfying load and generation constraints. An Adaptive Modified Particle Swarm Optimization **(**AMPSO**)** approach was developed in [7] to optimize the 24-hour operational scheduling of a microgrid comprising Distributed Generators (DGs) and BESS. Similarly, [8] proposed a Mesh Adaptive Direct Search (MADS) framework for operating strategy determination and operating cost minimization in a hybrid microgrid environment. Model Predictive Control (MPC)-based optimization framework is presented in [9-10] to determine the optimal size of BESS that maximizes the *total profit* from wind power firming. The study highlights that incorporating an MPC scheme and enables dynamic decision-making that accounts for forecasted wind power variability and market prices, leading to better economic performance compared to static scheduling methods. An adaptive modified firefly algorithm (AMFA**)** was developed in [11] to manage **the** operational uncertainties of distributed generators (DGs) and energy storage devices within the microgrid. This metaheuristic approach enhances the convergence speed and avoids local minima, providing robust and near-optimal solutions for cost-effective operation and optimal sizing of the storage units under stochastic conditions.

Linear/Integer Programming and Mixed-Integer Linear Programming (LP/MILP) when non linearities are linearized are used when tractability is needed and data are deterministic and are widely applied for techno-economic optimization and planning [13]. Scenario-based stochastic programs or chance-constrained formulations to capture renewable and load uncertainty improve out-of-sample economic performance but increase computational cost [14]. [15] propose KKT reductions and heuristics for detailed battery degradation, converter nonlinearities, or market interactions; sometimes invoked as bi-level problems (planning upper level, operational scheduling lower level[16].

[12] utilized the Particle Swarm Optimization (PSO) technique to determine the optimal size of BESS aimed at minimizing the microgrid operating cost. The proposed method leverages peak load levelling and energy-saving strategies to reduce both the total energy cost and peak demand charges. The PSO-based approach effectively balances computational simplicity and accuracy, demonstrating significant cost reductions when compared to heuristic or deterministic methods While these approaches offer some degree of promise, degradation cost is either completely ignored or models based on cycle life or calendar life are adopted, which are not useful in expressing the truly real-time operational conditions. On the other hand, throughput-based degradation models are able to offer a better operational representation for microgrid cost optimization and lifetime prediction, estimating cost and lifetime as a function of the total energy discharged [14-16].

The present study attempts to fill this uncertainty gap by developing a throughput-based degradation model for a BESS within a hybrid renewable energy microgrid. The proposed framework outputs average kWh throughput, total MWh discharge, degradation costs, and BESS lifetime and then integrates them within a cost optimization problem. The objective is to minimize microgrid operating cost (OC) in conjunction with the cost of electricity (COE) while guaranteeing reliable power dispatch from DGs and BESS. Predicted power from wind, PV, and microturbine drops are used over a 24-hour time horizon, and four optimization algorithms, LP-IP, PSO, APSO, and M-JAYA, are deployed for comparative evaluation. Our study's uniqueness is found in its dual-objective cost framework, throughput-driven degradation model, and comparative optimization approach using LP-IP, all of which work together to create a methodology for BESS sizing and operation in hybrid mcrogrids that is more precise, economical, and practically implementable.

The present paper is organized as follows: Section 2 describes the microgrid topology and component modeling. Section 3 includes the problem formulation and BESS degradation simulation parameters. Section 4 entails the problem optimization and algorithmic implementation. Section 5 closes with a discussion and comparison of results, including operating cost, electricity cost, and degradation parameters. Section 6 summarizes the study and describes scope for future research, followed by references in Section 7.

2. System model and configuration

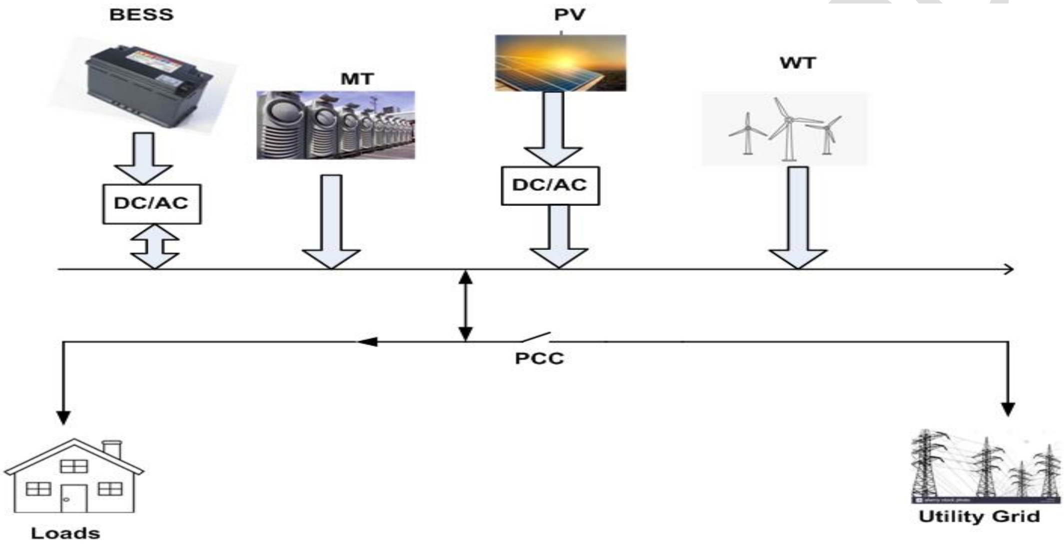

Fig .1. Test system consisting of Hybrid DGs and BESS in microgird

The discussed energy management framework is based on a grid-tied residential microgrid that interfaces with multiple HRES along with the BESS. The Renewable Generation Units comprise PV panels, WTs, and MTs as viewed in Fig. 1. The inverter operates on a bidirectional mode to enable power conversion from DC to AC or vice versa, whereby energy stored in BESS can be dispatched into the utility grid during peak demand or local load support. The control strategy of the operating system is dictated by minimum and maximum states of charge of BESS, which forbids the overcharge or deep discharge of the battery to prolong battery life and safe operation. So, it is an optimization system against operating costs and costs of electricity considering degradation effects and lifetime constraints of BESS under reliable load demand.

Islanding of the microgrid starts if an outage occurs in the grid and it can be islanded manually or automatically depending on load characteristics and system capacity. Manual islanded operation, mainly identifiable in hardly large or complex installations like hospitals, hotels, and manufacturing plants, consists of load prioritization carried out by the operator. Priority loads are connected dynamically depending on operational requirements during daytime, nighttime, or seasonal variations. On the other hand, automatic islanded operation offers a fast and seamless transition from grid disconnection through electronically controlled circuit breakers. This way is preferable for sites with single buildings such as a residential house or a supermarket where easy load distribution allows the microgrid to meet demands for base and peak.

In general, islanded operation is adopted for disaster recovery or emergency situations given that it is technically and economically less feasible for a standalone system to operate perpetually. However, the system can indefinitely sustain critical loads until restoration of grid service, provided the BESS is adequately sized and resources are scheduled properly. On reconnection, the microgrid switches back to grid-tied mode without compromising supply reliability. This dual-mode operation thereby ensures that the proposed system can provide continuously, highly reliable power during both normal and contingency situations, thus solidifying resilience and improving the overall efficiency of energy management at a residential level.

2.1 Modelling of Photovoltaic system

A photovoltaic (PV) system in the proposed microgrid environment constitutes part of the hybrid renewable energy sector for conversion of solar radiation into electrical power. Being highly dependent on sunny irradiance and with its statistics in turn subject to considerable temporal variability arising from weather conditions and environmental factors, the PV power output is stochastic in nature, and thus it requires accurate modeling so as to guarantee its reliable energy management with integration into other Distributed Generation (DG) units and the Battery Energy Storage System (BESS).STC and NOCT are then referenced for achieving accurate modeling. STC assumes an irradiance of 1000 W/m², a cell temperature of 25°C, and an air mass of 1.5. NOCT, however, represents more reasonable operating conditions with respect to ambient temperature and actual irradiance levels. Depending on temperature, the temperature coefficient further affects the performance of PV modules because it accounts for output reduction at higher temperatures[17-18].The PV system could extract the optimum energy with varied solar conditions with help from the Maximum Power Point Tracking (MPPT) controller. The MPPT sets the PV array operating point dynamically under all conditions of irradiance and temperature to deliver maximum power to the microgrid or battery storage.

The instantaneous electrical power output (t)-of the PV system at time t is obtained from the following relation:

$$P_{PV}=P_{STC}.\ (G_C/G_{STC})\ [1 + k\ (T_C - T_{STC})] \qquad (1)$$

Where PSTC is the rated power of a PV module at STC, G_C is the solar irradiance on the working plane of the PV system (kW/m²), G_{STC} is the irradiance at STC (1 kW/m²), TC is the cell temperature, T_{STC} is the temperature at STC, and k is the temperature coefficient of power.

The model provides a robust framework to forecast photovoltaic power generation under varying environmental conditions and will thus serve as input for the optimization of energy dispatch in the hybrid microgrid system.

2.2 Modelling of Wind power system

Wind energy conversion interprets the kinetic energy of moving air masses into the mechanical energy by means of a wind turbine, which is then converted into the electrical energy through a generator. Mainly, it is wind speed to determine the power generated by the wind turbine and that cannot be held constant due to meteorological and geographical restraints [19-20]. The truly random nature of wind speed thus calls for an adequate modeling scheme for enhancing predictive capabilities on power generation and aiding in the effective coordination of other DG-type generation units along with the BESS.Wind harnessing is proportional to the cube of wind speed; therefore, any small variation in the velocity can translate into huge fluctuations in power output. The relationship between the electrical power and the wind speed is governed by parameters specific to the turbine, cut-in speed (minimum wind speed required to generate power), rated speed (wind speed at which maximum rated power is achieved), and cut-out speed (wind speed beyond which the turbine ceases operation to prevent mechanical damage). These parameters characterize the performance of the turbine under given environmental conditions.At time t, the electrical power output P_{WT} of a wind turbine can be expressed as follows:

$$P_{WT}= \left.\begin{array}{ll} a + b*V_w & V_{ci} \leq V_w \leq V_r \\ 0 & V_w \leq V_{ci} \, , V_w \leq V_{co} \\ P_r & V_r \leq V_w \leq V_{co} \end{array}\right\} \quad (2)$$

Where $a = (P_r \ . \ V_{ci}/V_{ci} - V_r)andb = (P_r/V_r - V_{ci})$

V_{ci} , V_{co} , V_w and V_r are the cut in, cutout, nominal and rated wind speeds respectively. The behavior of wind speed can be simulated by using Weibull distribution function.

This piecewise function considers the turbine's operation limits for a proper depiction of the power curve. When combined with real- or forecasted wind speed data, the system can estimate hourly energy contributions from wind power to include in the overall optimization framework for the hybrid renewable energy microgrid.

2.3 Modelling of Microturbine

Microturbines are compact single-stage combustion turbines that find various applications for distributed generation due to the ability to ensure production of reliable power of some kilowatts to several megawatts. In construction, microturbines are simplified versions of gas turbines with a rotating turbine and compressor and usually fuelled by natural gas, diesel, and biogas. Their modularity and efficiencies at partial load as well as their capability of CHP make them appropriate choices for hybrid renewable microgrids, especially at the residential and small commercial level [21].

In a hybrid framework, microturbines are treated as controllable power sources that complement variable renewable energy units such as PV panels and wind turbines. In contrast to renewable units whose power output cannot be controlled, a microturbine's power output can be controlled, within operational limits, according to load requests and fuel availability to provide the much-needed quick assessment of-demand fluctuations. Indeed, the operating cost of a microturbine depends on fuel consumption as well as maintenance cost, for which proper cost modelling should be adopted for optimization. In this study, the power output of the microturbine is assumed to change randomly between minimum and maximum operational limits, thus describing the real power load-following operation of the microturbine [22-23]. The cost function of the microturbine power is assumed to be a linear function expressed as:

$$C\ (P_{MT}) = a + b\ P \tag{3}$$

where CMT is the cost of power generation (in \$/kWh), P is the output power expressed as a fraction of the rated capacity of the turbine, while a and b are parameters of the cost function and were taken as 0.0325 and 0.014, respectively [29].
This cost function has been integrated into the overall optimization framework of the microgrid so that its operating costs can be assessed under various dispatch strategies. By taking advantage of the predictable behavior of microturbines and the stochastic nature of renewable outputs, the hybrid system can provide better levels of reliability and cost efficiency. The flexible operation of the microturbine supports microgrid performance when solar or wind generation is low and bridges operation between grid-connected and islanded modes.

2.4 Modelling of Lithium Ion Battery Energy Storage Systems

Battery Energy Storage Systems are considered very important in view of actually operating a microgrid with an intermittent renewable DG and backup power to ensure load reliability. Batteries during storage absorb surplus power during low-demand periods and discharge during high demand, increasing system stability and otherwise reducing costs for power in the customer's cost calculation. Li-ion batteries stand very popular among many kinds due to their excellent energy density, long cycle life, extremely low self-discharge, for islanded and grid-connected microgrid

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operations[24-25]

The degradation characteristics determine the performance and economics of Li-ion Battery Energy Storage Systems, thus relevant to its lifetime and operating cost. A battery degrades by aging through charge-discharge cycles, therefore, degradation is strongly related to the energy throughput over time. Hence degradation modeling becomes inevitable since it is used to assess lifetime costs and optimizes microgrid operation.

In this case, the Li-ion battery is proposed to be represented by throughput-based degradation parameters, restricting charge and discharge rates hourly. Energy stored to or supplied by a battery at time t is always constrained by its minimum and maximum capacity limits to always ensure that the battery is not under unsafe or undesirable operating conditions such as overcharging or deep discharging.

2.4.1 Charging mode:

$$C_{BES,t+1} = \min\{(C_{BES,t} - \Delta t P_{BES,t})\eta_c,\ C_{BES\ min}\} \tag{4}$$

$$P_{BES\ charge(t)} = \max\left\{P_{BES\ min},\ (C_{BES,t} - C_{BES\ max})\frac{\eta_{charge}}{\Delta t}\right\} \tag{5}$$

2.4.2 Discharging mode:

$$C_{BES,t+1} = \max\left\{\left(\frac{C_{BES,t} - \Delta t P_{BES,t}}{\eta_d}\right), C_{BES\ min}\right\}$$

$$P_{BES\ discharge(t)} = \min\left\{P_{BES\ max},\ (C_{BES,t} - C_{BES\ min})\frac{\eta_{discharge}}{\Delta t}\right\} \tag{7}$$

$P_{BES\ charge}$ and $P_{BES\ discharge}$ are the charge and discharge powers at each hour instant wrt P_{BES}. P_{BESmin} and $P_{BES\ max}$ are minimum and maximum BESS capacity limits in terms of power. C_{BESmin} and C_{BESmax} are the minimum and maximum stored energy capacity limits of BESS.η_{charge} and $\eta_{discharge}$ are the charge and discharge efficiencies, which plays a significant role in delivering discharging power to the load.

2.5 Utility grid

The utility grid acts as a secondary source of supplying power to meet the promissory of 24 hours of load demand of the microgrid. During grid-connected mode, any deficit created from renewable generation and BESS output is met with power drawn from the grid. Load-one-fifty forecast mode supply and DG dispatch and BESS dispatch are optimized for supply reliability to minimize use of grid power. The BESS-size is dynamically adapted to load changes for each hour to increase reliability and operational efficiency. Such an integrated approach helps to reduce microgrid operating costs, leading to continuity of supply against ever-changing demand conditions.

3. Problem formulation of microgrid operating cost with BESS degradation cost and electricity cost

In this work, a microgrid system based on HRES comprises essentially two wind turbine units, two PV units, two MT units, and a BESS. This configuration is conceived to supply the forecast hourly load demand with a view to enhancing supply reliability and minimizing utility grid dependency, thus minimizing electricity cost for the consumer. The proposed microgrid is supposed to meet the average load demand of about 1.78 kW through optimal dispatch of DGs and BESS, explicitly considering the degradation of the batteries.HRES, for microgrid, basically means continuous availability of power; proper load management; better system efficiency; and less maintenance of the system due to minimum servicing requirements. These benefits have therefore led the HRES to gain popularity in small-scale microgrid implementations involving residential, office, and similar low-power demand situations.

In this study, the optimization target was set at minimizing the total operating cost of the microgrid, including DG operation and maintenance cost, BESS degradation cost, and TDC of energy supply, while reducing electricity prices for consumers in grid-connected mode through the fast and smart utilization of renewable resources and storage.

$$\mathbf{Min(O.C)_{MG}} = \sum_{t=1}^{T}\{\mathbf{D.G_{cost}} + \mathbf{Grid_{cost}} + \mathbf{(C)_{BESS}} + \mathbf{DEGC_{BESS}}\} \quad (8)$$

$$\mathbf{Min(O.C)_{MG}} = \mathbf{Min}\sum_{t=1}^{T}\left(\mathbf{C_{P-DG}} + \mathbf{OM_{DG}} + \mathbf{C_{grid}} + \mathbf{(C)_{BESS}} + \mathbf{DEGC_{BESS}} + \mathbf{RC_{BESS}}\right) \quad (9)$$

The operational cost of the microgrid is one that embraces respective costs paid on Distributed Generators, grid power, and BESS degradation as presented by equations (8) and (9) as the objective function. The cost components such as DG_{Cost} and C_{BESS} relate to the energy supplied by the DG and BESS, operation and maintenance cost (O&M), replacement cost (RC) , $\mathbf{DEGC_{BESS}}$ reflects degradation cost and Costs for electricity supplied from the grid are referred to C_{grid}. The BESS degradation cost is another important aspect, $DEGC_{BESS}$, which considers aging caused by charge–discharge cycles using throughput-based modeling. The degradation time calculations and life estimations outlined by Equations (10)–(12) are embedded into the operating cost formulation to generate an operationally cost-optimized solution with satisfactory system disruption reliability [26-27].

$$\mathbf{DEGC_{BESS}} = [\mathbf{W} * \mathbf{C_{BESS-Max}}] \quad (10)$$

The parameter W indicates the degradation cost for the Battery Energy Storage System (BESS) in Rs/kWh, derived from simulations using the average energy throughput and the initial cost of the battery. This value is added to the total operating costs to account for the aging of the battery from an economic perspective.

$$\mathbf{BatteryDEG - Cost(W)} = \left\{\frac{\mathbf{intialinvestmentcostofbattery(Rs)}}{\mathbf{AveragekWhrthroughputofbattery}}\right\} \quad (11)$$

The degradation-based lifetime (LT) of the BESS is considered for its actual kWh throughput from the simulations and its average lifetime throughput specified by the manufacturer. The relationship is expressed mathematically through Equation (11), which is then used in the formulation of Total Day Cost to arrive at a proper lifetime-based cost.

$$\mathbf{Battery_{LifeTime}(Years)} = \left\{\frac{\mathbf{TotalactualMWhthroughputforyear}}{\mathbf{TotalaveragelifetimeMWh}}\right\} \quad (12)$$

BESS total day cost (TDC) is implicit in Equation (13) and after taking degradation hazards into account, the total last cost functionally will be formed by Equation (14).

$$\mathbf{(TDC)_{BESS}} = \frac{\mathbf{C_{BES,Max}}}{\mathbf{365}}\left\{\frac{\mathbf{IR(1+IR)^{LT}}}{\mathbf{(1+IR)^{LT}-1}} * \mathbf{FC} + \mathbf{MC} + \left(\mathbf{C_{BES,Max}} * \frac{\mathbf{RC}}{\mathbf{(1+IR)^{LT}}}\right)\right\}$$
(13)

$$\mathbf{(T.C)_{BESS-DEG}} = (\mathbf{W} * \mathbf{C_{BES-Max}}) * \mathbf{(TDC)_{BESS}} \quad (14)$$

In computing the TDC for BESS, the average kWh throughput and real MWh throughput stand out as pivotal components for proper cost estimation. An accurate depiction of degradation would demand hourly simulations of different rates of battery discharge and could be contrasted with actual discharge profiles from the model. The total cost of electricity (COE), given in Rs/kWh and expressed in equation (15), is minimized subject to the load demand being completely satisfied. This cost of electricity is then multiplied by instantaneous load demand to obtain the electricity cost at each time step.

$$\mathbf{CostofElectricty(COE)} = \frac{\sum_{t=1}^{T}(\mathbf{C_{PV}} + \mathbf{C_{BESS}} + \mathbf{C_{MT}} + \mathbf{DEG_{BESS}})}{\sum_{t=1}^{T}\mathbf{P_L}} \quad (15)$$

The maintenance cost equation for the DGs over the time horizon T is said to be a summation of all maintenance costs of the DGs during every operating interval, stated as equation (16).

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$(MC)_{DG}$=[$(MC)_{WT1}$+$(MC)_{WT2}$ +$(MC)_{PV1}$ + $(MC)_{PV2}$ + $(MC)_{MT}$]* T(16)

3.1 Constraints

The microgrid system with HRES and BESS is affected by inequality constraints.

3.1.1 DGs constraints

$P_{WT1\text{-}Min} \leq P_{WT1} \leq P_{WT1\text{-}Max}$ (17)

$P_{WT2\text{-}Min} \leq P_{WT2} \leq P_{WT2\text{-}Max}$ (18)

$P_{PV1\text{-}Min} \leq P_{PV1} \leq P_{PV1\text{-}Max}$ (19)

$P_{PV2\text{-}Min} \leq P_{PV2} \leq P_{PV2\text{-}Max}$ (20)

$P_{MT\text{-}Min} \leq P_{MT} \leq P_{MT\text{-}Max}$ (21)

The limits imposed set forth the minimum and maximum power-capacity constraints within which Distributed Generators must operate. Meeting these constraints ensures that predicted load demand is fulfilled. The integrated operating cost and cost of electricity functions are optimized, subject to full adherence to the DG capacity limits throughout the entire scheduling horizon.

3.1.2 BESS constraints

$P_{BESS\text{-}Min} \leq P_{BESS} \leq P_{BESS\text{-}Max}$ (22)

$SoC_{Min} \leq SoC_{BESS} \leq SoC_{Max}$ (23)

From a sizing perspective, LI BESS is optimized with power capacity ranging from 50 kW to 500 kW and energy storage of 500 kWh for economic operation of the hybrid microgrid. One of the key issues in such optimization is that of estimation of SoC that shows the present level of energy stored in a battery. The SoC is required to be within the unit-ranged 0-to-1 for its correct working wherein 0 denotes fully discharged whereas 1 stands for fully charged states. Real-life working conditions would have LI BESS charging or discharging between 80 and 95 percent SoC, feeding on this window due to its energy density, steady power discharge, and extended cycle life [28-29].

In this research, BESS degradation cost analysis is carried out by estimating the lifetime from hourly discharge profiles while maintaining the SoC within prescribed limits; at about 35 percent SoC, accelerated aging sets in, with renewals possibly needed within its operational life. Hence, for minimum operating costs of the microgrid and to ensure system reliability as well as battery life, accurate determination of BESS size in terms of both average and actual energy throughput (kWh) is very essential.

3.1.3 Grid Constraints

A function of precision enhancement is ascribed to this cost in optimizing the efficient operations of the microgrid. Once power flow has been dispatched from the DGs and BESS, the grid supplies any remaining load demand at the prevailing unit energy price [33]. Hence, this formulation has ensured that operational costs were modeled under resource conditions when loads are varied. The power exchange between the grid and microgrid is bounded by maximum and minimum power limits at each time step and is mathematically stated as follows:

$P_{grid\text{-}Min} \leq P_{grid} \leq P_{grid\text{-}Max}$ (24)

4. Implementation strategy with heuristic and LP-IP optimization algorithms

Operating profiles and electricity costs are minimized and functions accounting for battery degradation and lifetime technically are solved using heuristics and a Linear Programming Interior Point (LP-IP) solver. The LP-IP technique provides better optimality in scheduling cost minimization compared to heuristics. Under heuristic optimization techniques, Particle Swarm Optimization (PSO), Accelerated Particle Swarm Optimization (APSO) and MJAYA algorithms are used to solve the objective. Linear Programming and interior point (LP-IP) solver based approach is used to solve the problem and compared with heuristic techniques to show the effectiveness of LP-IP solver. Results of operating cost and electricity bill minimizations, degradation costs and life time, average kWh and actual kWh throughputs of microgrid for 24hrs have been presented in a comparative analysis.

4.2 Accelerated Particle Swarm Optimization

An enhanced version of PSO, the Accelerated PSO (APSO), works with the global best (Gbest) only, to speed up convergence. With a Pbest and Gbest component, conventional PSO often can struggle to achieve better-quality solutions. Accordingly, to maintain diversity of search directions, APSO has removed Pbest and introduced some controlled randomness into the search process. This change tempers the shortcomings of the standard PSO by providing faster convergence and better optimization capabilities. The velocity update of APSO includes a random factor and is given in [30].

$$\mathbf{V_{i+1} = V_i + (\alpha * R_1) + R_2 * (G_{best} - X_i)} \quad (27)$$

In APSO, the random variables R_1 and $R_2$are independently drawn from the uniform distribution in (0,1). To improve convergence even further, a monotonically decreasing function of randomness is introduced, defined as follows:

$$\boldsymbol{\alpha = \alpha_0 \gamma^t} (28)$$

Where $\alpha_0$is also called an initial randomness parameter and lies usually between 0.5 and 1. Product information, α_0=0.5, and t counts iterations. This approach slowly decreases the degree of randomness and helps efficiently converge while maintaining diversity. Simulation parameters include learning factors C1 = C2 = 2, inertia weight in the range $Wmax$ = 0.9 to $Wmin$ = 0.1, and overall 200 iterations.

4.4 Modified JAYA (MJAYA) Optimization

MJAYA optimization proposed in [31] is the modified version of original JAYA, to overcome the problem of premature convergence without trapping the solutions in local optima. The MJAYA optimization technique is the population based algorithm having

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only 2 control parameters of population size and total number of generations. The change in MJAYA algorithm compare to original JAYA is the change in the solution update equation, which overcomes the problem of premature convergence still present. In MJAYA algorithm, the solution having best fitness acts as a reference to all other members (good and worst solutions) to intensify their position towards near to the best fit solution. The position update equation of MJAY A algorithm is given by following equation (30).

$$\mathbf{X}'_{\mathbf{i,j}} = \mathbf{X}_{\mathbf{i,j}} + \mathbf{R}_1\left(\left|\mathbf{X}_{\mathbf{i,j}}\right| - \mathbf{G}_{\mathbf{best,j}}\right) + \mathbf{R}_2\left(\mathbf{G}_{\mathbf{worst,j}} - \left|\mathbf{X}_{\mathbf{i,j}}\right|\right) - \mathbf{M} \quad (30)$$

Where 'L' is the iteration coefficient. If R_1 and $R_2 > 0.5$ then L= 1 else L= -1.
The solutions obtained by MJAYA are superior and more effective than all other implemented optimization methods in solving the problem of operating and electricity cost minimizations considering the best and worst solutions of the objectives in obtaining optimal solutions.

4.5 Linear programming based interior point (LP-IP) solver

LP-IP solver is used to solve both linear and nonlinear optimization problems considering inequality and equality constraints as variables. LP-IP solver finds minimum of a function specified by following expression.

$$\min_x \ f(x) = \begin{Bmatrix} A.x \leq b \\ A_{eq} \ \ .x = b_{eq} \\ lb \leq x \leq ub \end{Bmatrix}$$

Where f(x), b, b_{eq}, lb, ub are vectors and A andA_{eq} are matrices. A and b corresponds to inequality constraints , $A_{eq}$and b_{eq} correspond to equality constraints and the lower bounds(lb) and upper bounds(ub) correspond to limits of the function which the objective is to be optimized. LP-IP based solver obtains optimal results because, the objective function will acts as a barrier which penalizes the non-feasible solutions by satisfying the inequalities $x \geq 0$ by using Karush- Khun- Tucker conditions[32-33], there by obtaining the minimized optimal solutions within the selected value of function tolerance. LP-IP solver method can handle the objective functions which are discontinuous by approximating the constraints of objective as a set of boundaries by changing them without reaching global minima. Therefore LP-IP solver algorithm is more accurate in solving the constrained minimization of the objective function within the bounds and converges to a global optimal solution.
The Linear Programming interior point method (LP-IP) relies on having linear programming model with objective function and all the constraints being continuous and twice continuously differentiable. LP-IP solver expresses the objective function

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with all the constraints, initial values, lower and upper bounds in the form of vector and matrices in a ‘linprog’ function and calls for Interior Point (IP) solver to execute the function. The syntax of LP-IP solver is given as in equation (32- 33):

$(X,f_{val},exitflag)=linprog(fun, A_{eq},b_{eq},A,b,lb,ub, options)$(32)

Options=optimoptions(‘linprog’,‘Algorithm’,‘interior-point’,‘display’,’iter’)(33)

The goal function uses a maximum of 200 iterations because the "linprog" function employs the interior point technique. "X" denotes the function's optimized value, and "fval" denotes the corresponding values of the objective function, where the best outcome was achieved. In this case, the LP-IP solver's maximum tolerance value is 1e-6. Because the LP-IP solver method converts the objective function to the standard form of LP-IP, it avoids the issues of implemented algorithms such as slow and premature convergence and stuck at local optima. This eliminates the non-feasible solutions that satisfy the constraint within the tolerance and maximum iteration count of the LP-IP solver algorithm method.

4.5.1 Algorithm of LP-IP solver-based approach

The proposed algorithm for microgrid operating cost and electricity cost minimization considering BESS degradation effect is described in the following steps.

1. Read the input data profile (DGs power generations, maximum and minimum capacity limits of BESS and Load profile)
2. Initialize population size and cost coefficients of BESS and DGs.
3. Develop and simulate the DGs and BESS scheduling algorithms and check for constraint violations.
4. After obtaining each sub algorithm's goal function values from step 3, initialize the assignment matrix using those values.
5. By incorporating the assignment matrix in an optimizer or solver to initialize the values of the objective function.
6. Verify that the LP-IP solver has all constraints, including equality, inequality, lower and upper bounds, and objective function matrix allocation..
7. If yes, then use function called ‘optimoptions’ by describing the algorithm type and uses ‘disp’ and ‘iter’ options to execute the solver.
8. Run the program using tolerance conditions, which shows the function's minimized value while meeting the limitations, and until the maximum number of iterations has been reached.

The other primary benefit of using LP-IP solver methods over other approaches is that they provide the majority of global minimum solutions without faltering at local optima and enhance the quality of the solution within the LP-IP solver's fixed iterations. In comparison to previous methods, this approach has a rapid convergence time and produces early convergence within

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the limited minimization of the constraints. Given the aforementioned benefits, we have used the LP-IP solver approach to accomplish the goals because it produces the best results in a shorter amount of time..

5. Results and discussions

A minimization of microgrid operational cost and that of electricity considering the effect of battery degradation over a 24-h schedule are discussed. The power outputs of the WT, PV, and MT units are simulated within the maximum rated limits for load and DG capacities [34-35]. The goal of the scheduling is to optimize operating and electricity costs, while fully satisfying the load demand. This is achieved through modeling the key BESS degradation parameters which include average and actual energy throughput (kWh), degradation cost, and battery life. By simulating the throughput on an hourly basis, one can accurately estimate the effect of battery aging for cost optimization and well-informed scheduling decisions for the hybrid microgrid.

Time(H)	PWT1 (kW)	PWT2 (kW)	PMT (kW)	PV1 (kW)	PV2 (kW)	Load (kW)
1.	659	687	428	0	0	1469
2.	697	706	439	0	0	1320
3.	698	697	365	0	0	1258
4.	666	575	452	0	0	1225
5.	668	673	447	0	0	1316
6.	717	672	347	0	15	1500
7.	710	692	531	10	71	1660
8.	710	731	496	66	88	1650
9.	714	745	503	97	115	1636
10.	705	686	507	121	139	1640
11.	677	659	363	137	152	1642
12.	697	637	372	144	162	1663
13.	698	560	349	142	160	1590
14.	693	650	400	132	154	1640
15.	700	651	599	118	132	1635
16.	697	656	137	93	106	1672
17.	700	661	380	60	82	1910
18.	698	658	617	15	45	1995
19.	644	667	651	0	1	2208

20.	673	663	703	0	0	2215
21.	675	660	743	0	0	2145
22.	687	641	695	0	0	1900
23.	692	673	710	0	0	1662
24.	671	647	710	0	0	1660

Table.1 Generation maximum limits on DGs and Predicted Load.

Hourly maximum output power of each DG and predicted load demand profile were given in Table 1. Here, our microgrid framework minimizes operating and electricity costs while respecting these generation constraints and meeting hourly load requirements. Power allocation is achieved in the optimal coordination of the DGs and BESS, with degradation effects of batteries explicitly taken into consideration. Accelerated Particle Swarm Optimization (APSO), MJAYA algorithm, and an IP-LP solver are used for solving the problem. A comparative analysis is conducted with respect to operational cost, electricity cost, and BESS degradation parameters between heuristics and the IP-LP technique. Optimum solutions provide one-hour throughput and degradation cost, with the BESS lifetime being estimated within power limits (minimum and maximum) for 24 hours. Results describe the better performance of the IP-LP solver in cost minimization as well as in resource exploitation.

Algorithm Type	Average throughput (discharge) (kWh)	Actual throughput (discharge)(MWh) for year	Attained Life Time(LT)years
APSO	396	3.480	3.13
MJAYA	412	3.616	3.32
LP-IP based solver	420	3.704	3.40

Table.2.Life Time comparisons with average and actual throughputs from BESS

Table 2 summarizes the comparison between BESS lifetime and the average energy throughputs corresponding to them and the actual energy throughput. It has been observed from the results that BESS lifetime is improved proportionally with throughput-based discharges; in other words, greater energy throughput implies longer operational life. Additionally, it can be inferred that the solver-based optimization technique outranks heuristic methodology in achieving the maximum lifetime of the battery and making the best use of throughput parameters.

Algorithm Type	Unit Cost of BESS based on degradation (Rs/kWhr)	Operating Cost(Rs) with BESS
APSO	100.50	6475
MJAYA	97.95	6356
LP-IP based Solver	95.20	6202

Table.3. Average degradation cost of BESS comparison with microgrid operating cost

Table 3 presents a comparative performance analysis pertaining to the BESS degradation cost and overall operating costs incurred by the microgrid. The degradation cost of the BESS is computed from equation (11), considering investment cost and average energy throughput (kWh). Presented with the degradation costs, the microgrid operating cost is then calculated accordingly. From the results, it is abundantly evident that the solver-based optimization technique manages to perform better than heuristic techniques, with lesser degradation and overall operating costs.

Algorithm	Operating cost of BESS without degradation effect (Rs)	Operating cost of BESS with degradation effect(Rs)
APSO	6403	6473
MJAYA	6223	6356
LP-IP based Solver	6160	6201

Table.4. Average microgrid operating cost comparison with and without BESS degradation effect

Table 4 presents the results for the microgrid operating cost, considering and ignoring the degradation effects of the BESS. As explained in equation (9), considering degradation cost adds an extra weight to the total operating cost formulation. Though the results indicate that operating costs go up when degradation is considered, the LP-IP solver has been able to produce lesser operating costs vis-à-vis heuristic methods, proving the solver's potential to dampen the cost implications of degradation and render superior cost optimization to the microgrid system..

Algorithm	Average cost of electricity without degradation effect (Rs)	Average cost of electricity with degradation effect(Rs)

APSO	13,115	12,970
MJAYA	12,876	12.804
LP-IP based Solver	12,842	12,742

Table.5 Electricity cost comparison with and without degradation effect

The degradation process introduces yet another factor in the microgrid operating cost-increasing total cost of operation. This arises from the fact that degradation expenses come in addition to system operation expenses. Nevertheless, the acknowledgment of degradation allows the operator to pick an optimum size of the BESS matching the load considered, which prevents future escalation of costs. The significance of degradation modeling lies in that, in terms of electricity cost, this remains beneficial; the higher energy throughput of the BESS under this method tends to reduce electricity billing, which can work to its advantage in cost reduction under various load conditions.

Algorithm	Average operating cost of BESS degradation effect(Rs)	Average cost of electricity with BESS degradation effect(Rs)
APSO	6475	12,975
MJAYA	6356	12,804
LP-IP based Solver	6201	12,746

Table.6.Average operating and electricity cost comparisons with degradation effect

Table 6. Clearly shows that the degradation effects really influence the minimization of operating and electricity costs. Among heuristics, JAYA comes closest to perfect theoretical solutions; but the LP-IP solver always does better than any heuristics in terms of theoretical optimization. The results also confirm that greater degradation parameters, including average kWh and actual MWh throughput, result in greater operating costs but lower electricity costs simultaneously. Degradation-based analysis for BESS sizing shall be entertained for the purpose of predicting replacement intervals accurately, which leads to the planning of costs and, consequently, the lessening of operational burden on the microgrid in the future and making the whole cost system more efficient in the long run.

Algorithm	SoC (Min %)	Soc (Max %)
APSO	6.4	83.2

MJAYA	8.6	91.4
LP-IP Solver	9.2	93.1

Table.7. Range of Minimum and Maximum values of State of Charge (Soc)

The minimum and maximum State of Charge values that define the charging state of the BESS are summarized in Table 7. It is very important for the SoC to be defined accurately as the sizing of the BESS depends directly upon it, with higher SoC implying more use of the stored energy so that the intermittent DGs and the utilities would be less involved in power generation, thereby reducing operating and electricity costs. For this paper, temperature effects on life cycles have been neglected, and degradation has been evaluated only in view of life, cost, and DoD. High DoD leads to accelerated aging of the battery; however, it has been confirmed that DoD does not go below 60% throughout the lifetime considered for evaluation.

BESS sizing, when taking degradation effects into account, becomes optimal in terms of balancing costs relative to benefits. Using the LP-IP solver, 428 kWh size for BESS has resulted as an optimal size for 550 kW capacity system in which the BESS would incur an operating cost of nearly Rs. 6221 for one day (24 hours). The results inferred that whenever smaller BESS sizes are taken, one has to bear higher operating costs, but a slightly higher cost with larger sizes is there to give a very low mismatch between generation and load demand.

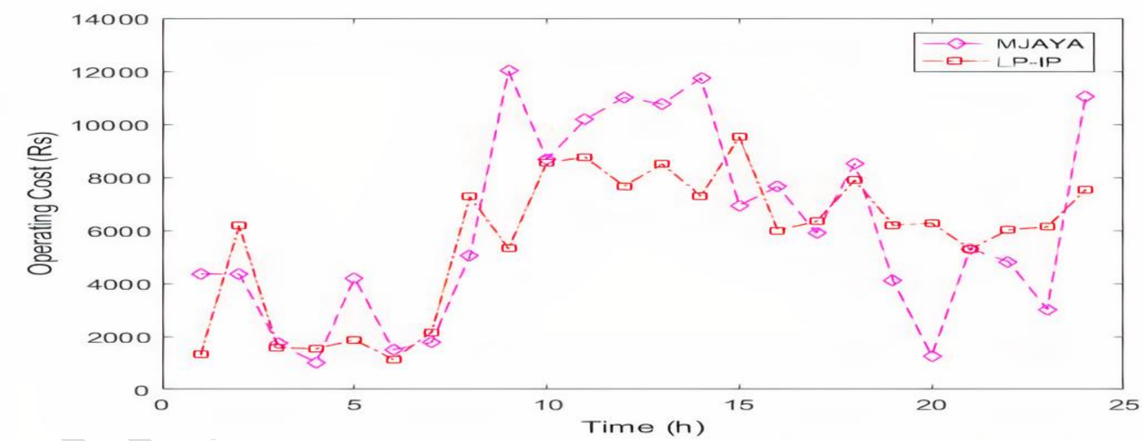

Fig.2. Operating cost of Microgrid Comparison with MJAYA algorithm and LP-IP solver

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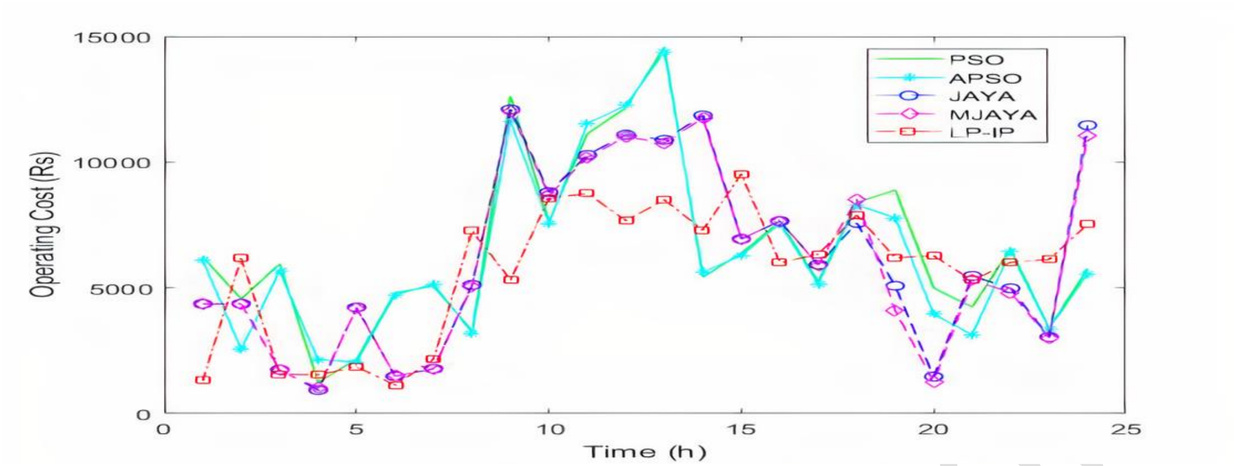

Fig.3. Operating cost of Microgrid comparison with heuristics and LP-IP solver methods

Figure 2 presents the side by side comparison between the Modified JAYA (MJAYA) algorithm and the LP-IP solver in the context of minimizing operating cost. The results show evidence proving that the LP-IP solver performs better than any other method considered, yielding the most optimal solutions in scheduling-based cost minimization problems.Figure 3 shows the universal comparison of all algorithms with respect to performance in cost reduction. Among the heuristic approaches, the JAYA algorithm seems to have yielded better results than other heuristics in most cases. Yet, the LP-IP solver, which aims to minimize the objective function in consideration of BESS degradation effects and satisfies load demand over the 24 hours horizon, is unavoidably the best among all heuristics.

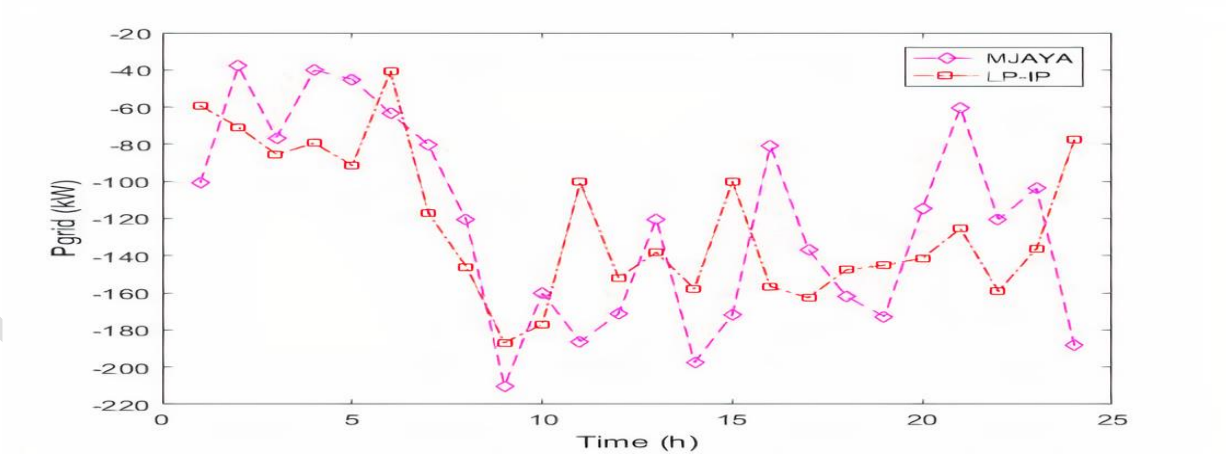

Fig.4. Error variation with MJAYA and LP-IP solver methods for 24hrs

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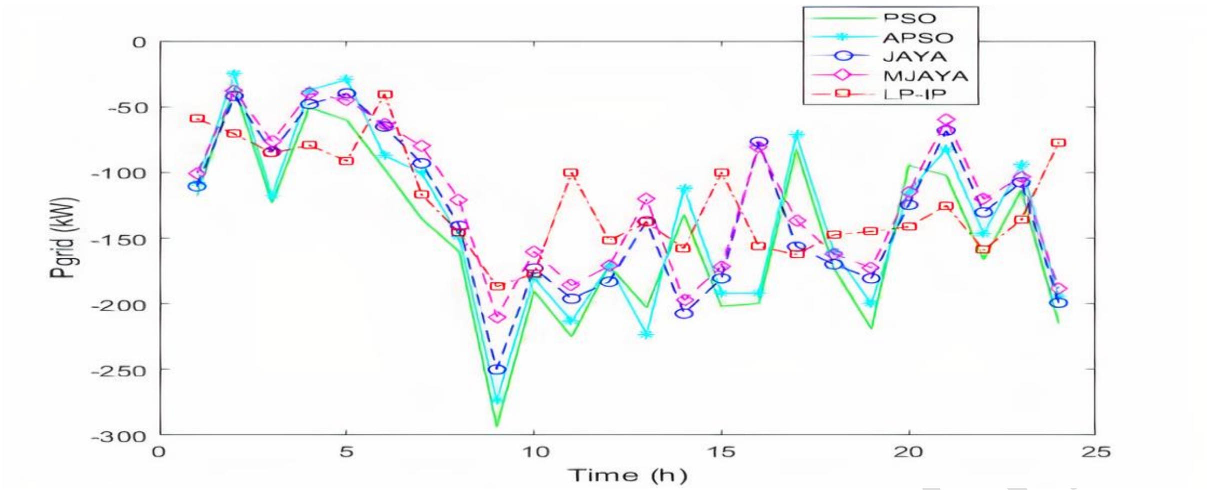

Fig.5. Error with comparison heuristics and solver methods for 24hrs

Simulation results of grid power drawn over a 24-hour horizon are presented in Figs 4 and 5 using the LMJAYA, heuristic methods, and LP-IP solver. Here, "error" is the residual supply that is drawn from the grid after power is dispatched by the DGs and BESS towards meeting load demand during cost optimization. Results suggest that LP-IP solver yields the minimum error in comparison with the heuristic approaches as it maximizes the total throughput of BESS while considering degradation effects. Tables 8 and 9 present the respective optimal power dispatch for DGs and BESS in grid-connected mode accounting and non-accounting for degradation effects. The results signify that the solver yields cost-efficient operation under all load conditions.

Time(H)	PWT1 (kW)	PWT2 (kW)	PMT (kW)	PV1 (kW)	PV2 (kW)	PBESS (kW)	PGRID (kW)
1	483.90	244.45	261.63	0	0	422.75	-57.3
2	499.33	506.29	208.88	0	0	42.27	-71.8
3	486.63	371.67	193.40	0	0	126.21	-84.5
4	274.83	357.46	114.15	0	0	404.11	-79.5
5	295.66	342.26	290.46	0	0	300.27	-90.4
6	537.41	296.11	364.88	0	0	271.19	-41.8
7	318.49	390.64	352.92	0	4.8277	484.26	-117
8	318.67	445.17	396.11	9.79	21.27	320.10	-144.1
9	377.90	330.64	391.24	41.11	16.51	300.34	-185.9
10	309.77	378.82	272.05	32.281	107.51	366.97	-176
11	306.85	352.26	280.38	109.53	77.32	429.17	-101.4

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12	429.16	415.53	368.87	114.36	100.391	86.68	-151
13	254.21	356.91	324.91	149.208	108.294	270.41	-138.5
14	382.92	326.47	314.56	94.245	150.010	217.74	-156.9
15	367.86	354.06	361.57	104.127	114.757	240.46	-100.8
16	371.25	311.54	424.14	25.626	90.217	298.43	-156.7
17	418.93	490.26	468.41	87.093	36.550	257.28	-161.6
18	427.17	504.80	432.01	46.272	1.382	442.26	-147.4
19	546.35	474.49	547.32	4.679	2.503	492.42	-145.3
20	539.54	527.21	541.58	0	0.7077	470.52	-140.4
21	550.94	495.51	537.42	0	0	441.27	-124.4
22	491.23	415.34	365.64	0	0	471.68	-158.2
23	310.69	457.92	298.61	0	0	365.42	-137.2
24	422.01	412.41	339.37	0	0	413.26	-76.5

Table.8. Optimal power discharges from DGs and BESS with degradation effect

Time(H)	PWT1 (kW)	PWT2 (kW)	PMT (kW)	PV1 (kW)	PV2 (kW)	PBESS (kW)	PGRID (kW)
1	483.91	245.45	258.65	0	0	428.75	-54.4
2	499.32	571.23	207.88	0	0	46.27	-65.8
3	486.6	622.6	193.4	0	0	128.21	-82.7
4	74.83	576.4	114.15	0	0	407.11	-80.8
5	296.6	249.2	292.46	0	0	306.27	-85.8
6	537.40	296.1	217.82	0	0	275.19	-37.3
7	417.49	490.64	462.91	0	4.8273	486.26	-114
8	519.67	546.17	360.11	9.79	21.27	324.10	-142.4
9	477.90	430.6	433.24	42.11	16.5	304.36	-182.7
10	409.78	478.83	377.06	32.280	108.51	366.98	-174
11	306.86	352.27	269.38	107.53	77.35	431.18	-98.5
12	429.18	550.5	368.87	115.36	100.39	90.68	-147
13	454.20	389.92	324.91	149.90	108.29	473.4	-135.1
14	482.9	426.47	408.55	94.247	156.67	220.76	-155.9
15	367.85	394.05	361.57	104.12	114.75	343.4	-98.1
16	371.25	511.5	513.15	25.627	90.217	300.4	-154.4
17	255.92	490.26	468.40	87.093	36.55	260.28	-160.1
18	427.18	504.80	463.00	46.272	1.38	445.27	-144.2
19	546.36	474.49	547.31	4.679	2.503	300.43	-143.1

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20	539.55	405.20	541.59	0	0.707	474.52	-139.3
21	550.90	595.52	558.45	0	0	445.27	-122.1
22	496.24	515.35	465.65	0	0	476.68	-155.6
23	410.62	557.96	598.63	0	0	402.42	-133.5
24	522.01	426.40	439.39	0	0	416.26	-72.5

Table.9. Optimal power discharges from DGs and BESS without degradation effect

The consideration of BESS degradation effects makes it possible to alleviate the utility's burden to some degree. Hence, under this consideration, both the microgrid operator and the end-user benefit significantly. Premature aging can be avoided by accurately estimating battery application lifetimes and degradation costs, thereby lessening electric bills and guaranteeing reliability. Correct sizing of the BESS under the HRES environment can guarantee power supply from a few kilowatts to several megawatts, especially in far-flung areas where lesser dependence on the grid is a serious constraint.Now, the LP-IP solver performs better because it converts the objective function into a constraint system (some call it "Presolve") and generates feasible initial solutions on the basis of Karush-Kuhn-Tucker (KKT) conditions to chop off the non-feasible regions. This way, it quickly reaches optimal power allocations down to minimum operating cost. The solver also treats discontinuous objective functions very well as constraints approximated to boundary conditions, so they can be re-evaluated in alternate operating scenarios. This approach guarantees global minima and hence makes the LP-IP solver very robust for constrained microgrid cost optimization.

Simulation Parameters	**Values**
Population size	50
Prediction horizon	24 hrs
Maximum number of iterations	200
BESS Power capacities	50 to 500 kW
Operating cost of PV	67 Rs/kWh
Operating cost of wind	60 Rs/kWh
Operating cost of MT	49 Rs/kWh
Wind Turbine ratings	0 to 700 kW
Microturbine ratings	0 to 700 kW
Solar PV ratings	0 to 150 kW
Grid power ratings	0 to 300 kW

Table.10. Simulation parameters and ratings of DGs

BESS parameters with Degradation effect	**Values**
Battery Capacity	500kWh

Battery Power Ratings	50-500 kW
Battery investment cost	45,000 Rs
Operation and Maintenance Cost	600 Rs/kWh
Replacement Cost	60 Rs/kWh
Total average life time specified for one year	1.2 MWh
Interest rate	0.06

Table.11. Simulation parameters for BESS with degradation effect

In Table 10, simulation parameters are given for Hybrid DGs and LI-BESS. The optimal operating and electricity costs are obtained considering the minimum and maximum bounds of power generation for the DGs and the BESS. Power outputs and throughput of DGs and BESS in hourly scheduling have to be within rated capacity to operate reliably and avoid overloading.Table 11 depicts the simulation parameters of BESS when degradation is taken into consideration. Using those parameters, degradation costs, and lifetime are computed based on battery investment costs and average total energy throughput (kWh). Then, this degradation cost is incorporated in the optimization framework to evaluate operating and electricity costs. The integration of BESS degradation modeling into the cost analysis of microgrids provides more accuracy and henceforth, a better ground for decision-making in DER-integrated systems.

The simulation was carried out for a grid-connected residential microgrid where the generation from PV, wind, and microturbine units, along with BESS dispatch, fully satisfies the hourly load demand under all constraint conditions (DG limits, SoC bounds, and grid power limits). This ensures the operational feasibility of the results. The results are presented with and without considering BESS degradation cost**.** The comparison clearly shows that including degradation in the optimization framework leads to a more accurate estimation of operating and electricity costs and provides longer effective battery life. This validates that the degradation-aware model better represents real operating condition.

6. Conclusions and future scope

Achieving reliable and economically feasible microgrid operation highly depends on appropriate battery sizing and cost-benefit analysis. This study proposed an optimization framework with the objective of minimizing microgrid operation and electricity costs while explicitly considering the degradation effect on life estimation. A Hybrid Renewable Energy System (HRES), combining wind, photovoltaic, and microturbine units with a Lithium-Ion Battery Energy Storage System (LI-BESS), was modeled and optimized using heuristic algorithms, such as APSO, MJAYA as well as a

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Linear Programming Interior Point (LP-IP) solver. Simulations for a 24-hour period revealed the LP-IP solver to be superior to all other heuristic methods while also producing the least operating and electricity cost results and meeting the load demand. The LP-IP solver achieved the lowest total operating cost of Rs. 6202, outperforming M-JAYA **(**Rs. 6356**)** and APSO **(**Rs. 6475**),** while also producing the minimum average cost of electricity **(**Rs. 12,742**)** and extending BESS lifetime to 3.40 years compared to 3.32 years (M-JAYA) and 3.13 years (APSO). The degradation cost was found to be lowest for LP-IP at Rs. 95.2/kWh, confirming its superior optimization capability. Results further revealed that higher BESS throughput (396–420 kWh daily, 3.48–3.70 MWh annually) increases operating cost marginally but enhances lifetime and reduces user-side electricity cost. The proposed throughput-based degradation model also determined an optimal BESS capacity of approximately 428 kWh for a 550 kW hybrid system**,** satisfying all technical constraints and achieving reliable power supply. Overall, the results validate that degradation-aware optimization provides more accurate economic planning, improves BESS utilization, and supports sustainable microgrid operation, with the LP-IP solver emerging as the most effective and computationally efficient approach. Future research will improve this framework by considering calendar-life and capacity-based degradation models, incorporating DoD and SoC variations, and investigating HESS to yield enhanced performance and further cost reductions.

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