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RESEARCH ARTICLE

Advanced Genetic Algorithm for Optimal Microgrid Scheduling Considering Solar and Load Forecasting, Battery Degradation, and Demand Response Dynamics

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ABSTRACT Microgrids driven by distributed energy resources are gaining prominence as decentralized power systems offering advantages in energy sustainability and resilience. However, optimizing microgrid operation faces challenges from the intermittent nature of renewable sources, dynamic energy demand, and varying grid electricity prices. This paper presents an AI-driven day-ahead optimal scheduling approach for a grid-connected AC microgrid with a solar panel and a battery energy storage system. Genetic Algorithm generates demand response strategies and optimizes battery dispatch, while LightGBM forecasts solar power generation and building load consumption. The approach aims to minimize operational costs and ensure microgrid sustainability, using a battery degradation cost function to extend its lifespan. Simulation results conducted in the University of Moratuwa microgrid show a significant 14.22% decrease in electricity costs under Sri Lanka's current tariff structure, attributed to intelligent energy dispatch scheduling. Proactive demand response management has the potential to minimize costs further. This research contributes to microgrid optimization knowledge, promoting the adoption of intelligent and sustainable energy systems.

INDEX TERMS Microgrid, optimizing, genetic algorithm, machine learning, decision trees, demand response strategies, renewable energy, battery energy storage, sustainability.

NOMENCLATURE

GENERAL TERMS

- BESS - Battery Energy Storage System, used for storing electric charge for later use.
- DR - Demand Response, strategies to adjust demand for power instead of adjusting the supply.
- GA - Genetic Algorithm.
- PSO - Particle Swarm Optimization Algorithm.

VARIABLES AND PARAMETERS

- P_{net} - Net load, the difference between power consumption by the building and power produced by solar panels.
- C_d - Total cost for a given day, including electricity cost, battery degradation cost, and DR penalties.
- $E(X_1)$ - Electricity cost function.
- $B(X_1)$ - Battery degradation cost function.
- $P(X_3)$ - Demand Response (DR) penalty function.
- SOC - State of Charge, representing the current energy level as a percentage of its maximum capacity.
- DoD - Depth of Discharge, indicating the percentage of battery energy used.

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- ΔSOH - Change in State of Health of the battery.
- Q_{MAX} - Maximum rated charge of the battery (Deprecated, use Q^{MAX} instead).
- N_{cycle} - Number of life cycles of the battery.
- I - Charging/discharging current.
- $c-rate$ -A measure used to describe the rate at which a battery is charged or discharged relative to its capacity. It is defined as the current in amperes (A) that is either charged or discharged from the battery, divided by the battery's capacity in ampere-hours (Ah).
- SOH - State of Health.
- Q_{t0} - State of Charge (SOC) at t_0.
- Q_{t1} - State of Charge (SOC) at t_1.
- Q^{MAX} - Maximum rated charge of the battery, supersedes Q_{MAX}.

INDICES AND SETS

- t - Time slot index.
- T - Total number of time slots in a scheduling horizon.
- i - Index for flexible loads.
- M_1, M_2 - Number of Type I and Type II flexible loads, respectively.

I. INTRODUCTION

This research is an extension of our previous work [1]. This significantly extends the research presented in the previous work [1] by providing a detailed analysis of battery degradation modeling, And it introduces an enhanced genetic algorithm with a novel crossover operation and warm restart capability, leading to more effective optimization of the microgrid's operational strategy. Additionally, this paper explores a wider range of forecasting algorithms, further refining the prediction accuracy for solar power generation and load consumption. These advancements collectively contribute to achieving higher cost reductions.

The transition towards sustainable energy systems is vital for combating climate change and reducing dependence on fossil fuels. The importance of renewable energy in addressing climate change and decreasing our dependence on fossil fuels positions microgrids as a pioneer of sustainable power systems. They play a crucial role in improving the stability and reliability of local networks, especially when dealing with the unpredictable nature of renewable energy sources like solar and wind, as well as varying power consumption patterns.

Since microgrids can incorporate renewable energy sources, they lower greenhouse gas emissions [2] aand advance sustainability at the local level by utilizing solar, wind, or other clean energy technologies [3]. In addition, Microgrids enhance the resilience and reliability of electricity supply, catering to dynamic consumption patterns through a mix of energy sources [3], [4]. Figure 1 [5] illustrates a microgrid system, exemplifying such an integrated approach. Additionally, microgrids provide the adaptability to integrate cutting-edge technologies and energy management techniques, like energy management optimization and demand response, enabling more effective and reliable energy systems.

A microgrid is an independent energy system that works connected with a larger power grid or in islanded mode. The autonomy of microgrids allows islanded operations [6]. It can, in other words, disconnect from the main grid and keep supplying power to its neighborhood [6]. This ability is especially useful in times of grid disruption or emergency because the microgrid can keep running life-saving facilities like hospitals, schools, or emergency response centers. In addition to renewable energy sources these power sources often include conventional generators powered by diesel or natural gas [4] to ensure the reliability during emergencies. In Figure 2, it is presented an image showcasing the microgrid system at the University of Moratuwa.

The purpose of microgrids is to balance local energy supply and demand [7] reliably and optimally. They optimize electricity production and consumption using cutting-edge control and monitoring systems, ensuring effective operation and grid stability. A microgrid consists of a network of localized power sources, energy storage systems, and loads that are all controlled by sophisticated control systems [8]. Energy storage systems, notably batteries, play a pivotal role in reducing grid dependency and balancing energy supply [9]. A grid connected microgrid can minimize electricity cost by storing excess energy when demand is low(when main grid electricity prices are low) and releasing it during peak hours(main grid electricity prices are high). Energy storage devices, such as batteries, play a critical role since they can store and supply energy based on requirements [9], [10], [11], [12].

Microgrid optimization involves finding the most efficient and cost-effective way to manage energy resources within a microgrid [13]. The goal is to meet the energy demands of the microgrid while minimizing costs, maximizing reliability, and ensuring stable operation. This optimization process includes optimizing the allocation and utilization of available resources, such as battery charging, discharging, and load scheduling. By effectively managing energy, microgrids can reduce their operational costs while improving the reliability.

However, this optimization task is challenging and requires sophisticated approaches due to the various constraints associated with microgrid operation. This optimization problem faces hurdles such as the intermittency of renewable sources, electricity price variability, resource allocation, minimizing operational costs, and mitigating battery degradation [13], [14], [15]. In addition, the optimal scheduling solution must consider a range of constraints related to Microgrid operation to ensure smooth and effective energy management [16]. Finding the optimal solution involves considering factors such as load demands, resource availability, and operational limitations.

Several challenges and considerations are involved in microgrid optimization:

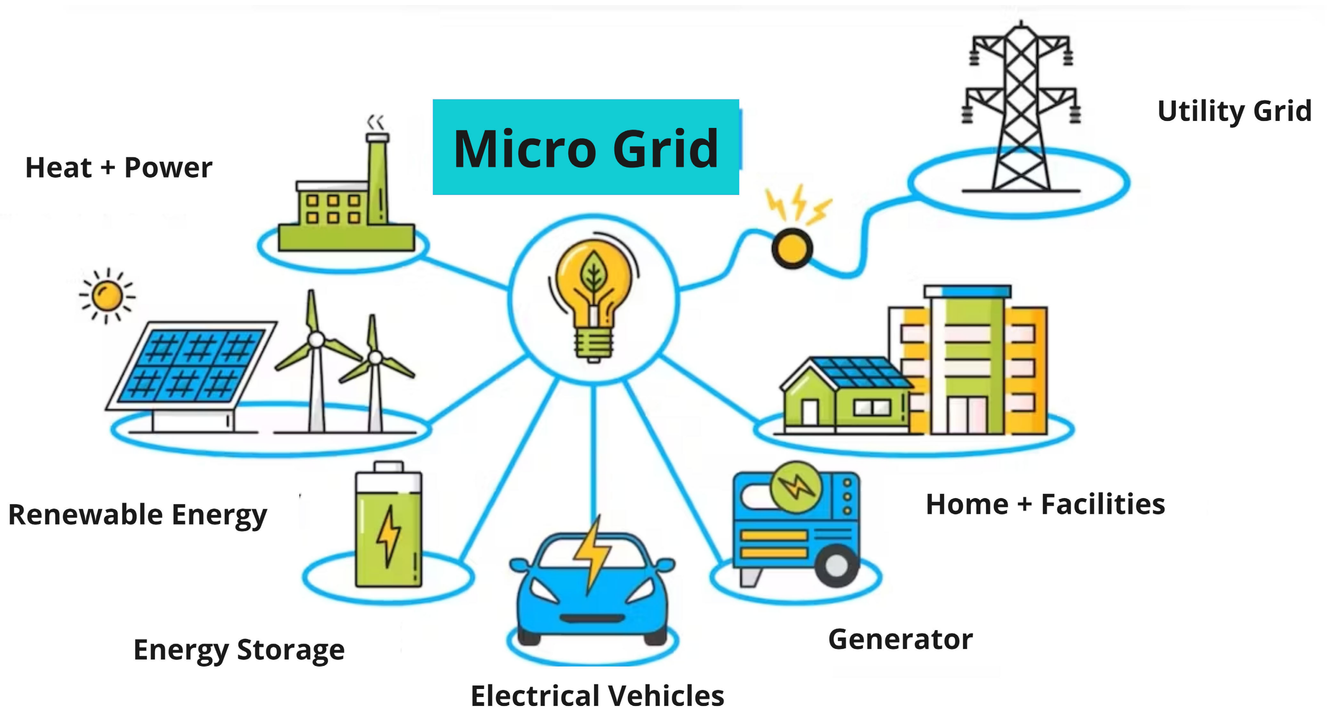

FIGURE 1. Illustration of a microgrid system. [5].

1) **Intermittency of Renewable Energy Generation**: The renewable energy intermittency and market dynamics together require sophisticated algorithms for energy forecasting and cost-effective energy management.
2) **Time variability of electricity prices**: Micrograds can be connected to the main grid to exchange energy when needed. The time variability of electricity prices is a challenge in microgrid optimization [14]. This involves aligning consumption with lower-priced periods and leveraging real-time data analytics [17].
3) **Resource allocation**: Microgrid optimization involves determining the optimal allocation of resources, such as battery storage and dispatchable generators, to meet energy demand effectively. This includes deciding when to charge or discharge the batteries, when to start or stop generators, and how to balance the load [14].
4) **Fuel Cost minimization**: Microgrid optimization aims to minimize the overall operational costs by optimally utilizing non-renewable energy sources such as diesel generators which have high fuel costs [17].
5) **Battery degradation**: Battery degradation is a significant challenge in optimizing microgrids. As batteries degrade over time, their performance and energy storage capacity decline. This leads to the need for costly battery replacement or refurbishment [15]. Addressing the effects of battery degradation is a significant challenge in microgrid optimization since the capital cost of the battery is considerably high.

Several approaches have been proposed to tackle challenges in microgrid optimization. Ross et al. [6] introduced a backcasting algorithm to address the intermittency of renewable energy generation and market dynamics, achieving a reduction of up to 8.14% in the average cost of energy. However, their approach primarily focuses on energy forecasting and cost optimization, neglecting considerations such as battery degradation and demand response dynamics. Goh et al. [18] formulated an energy optimization framework considering uncertainty in renewable energy and carbon trading markets. Their approach provides a stable operation scheme for microgrids and aids in reducing carbon emissions. However, their focus on uncertainty analysis leaves out considerations like solar and load forecasting, limiting the holistic optimization potential of the microgrid.

Yang et al. [19] developed a multi-objective optimal scheduling model for island microgrids, effectively addressing the uncertainty of renewable energy output and emphasizing the economic and stability aspects of microgrid operations. Nevertheless, their reliance solely on Monte Carlo methods for uncertainty estimation overlooks the potential benefits of incorporating advanced forecasting techniques. Wu and Wang [20] explored the integration of traditional methods with deep reinforcement learning (DRL) for microgrid energy management. While their approach shows promise in handling stochastic system dynamics, it lacks focus on load forecasting and scheduling, crucial components for effective microgrid operation and control.

Wen et al. [21] developed an optimal load dispatch model for community microgrids based on deep learning-based forecasting, showcasing improved forecasting performance and cost reduction of 8.97%. However, their separation of forecasting and optimization models highlights a gap in understanding the dynamic interaction between these components, crucial for real-time optimization.

Overall, existing literature has made significant strides in addressing various challenges in microgrid optimization, such as energy forecasting and uncertainty analysis. However, there remains a notable gap in comprehensive approaches that integrate forecasting, battery degradation, and demand response dynamics into optimization frameworks to achieve truly optimal microgrid scheduling. Among these challenges, the significant gap in existing research is the comprehensive consideration of battery degradation. Most studies overlook the impact of battery degradation on the efficiency and cost-effectiveness of microgrid operations. This oversight can lead to underestimation of operational costs and overestimation of system performance over time.

The day-ahead or week-ahead scheduling for microgrids relies on forecasted load consumption and power generation. The reliability of optimal schedule is thus highly dependent on the forecasting accuracy [22]. Forecasting uncertainties can cause the generated schedule to incur higher costs than anticipated, which can also make it challenging to balance the supply and demand of the microgrid effectively [23]. The difficulties of predicting power output and demand in microgrid systems are discussed by Dutta, et al. [22], particularly for renewable energy sources whose output is erratic and intermittent. The suggested strategy is based on the persistence method, which relies on historical power data instead of numerical forecasts. Traditional machine learning models for forecasting have limitations [24], such as requiring large datasets and having relatively low accuracy.

Deep learning-based forecasting can suffer from lengthy training times. As a result, Park, et al. [25] propose an accurate Multistep-Ahead (MSA) solar radiation forecasting model based on the gradient boosting machine (LightGBM). LightGBM is highlighted for its speed and accuracy in handling large datasets.

Many researchers have attempted to solve the optimal scheduling problem of a microgrid, but several challenges remain unaddressed. A hierarchical Genetic Algorithm (GA) and a Fuzzy Inference System (FIS) are used in Leonori, et al.'s work [26] to improve the efficiency of an Energy Management System (EMS) for energy exchange with the grid. They also incorporate a battery degradation cost model to aid in predicting the battery's remaining lifetime and reducing degradation costs.

Advanced optimization techniques are employed to tackle this complex problem and provide the most effective scheduling solution for microgrid energy management [16], [27]. Common optimization techniques used in microgrid scheduling include linear programming [28], Mixed Integer Linear Programming [28], genetic algorithms [29], and particle swarm optimization [30]. These methods help in balancing energy generation and consumption, minimizing costs, and ensuring reliable operation.

Genetic algorithms (GAs) offer several advantages over alternative methods. Unlike linear or quadratic programming, GAs can effectively capture nonlinear relationships and multiple conflicting objectives [31], making them suitable for multi-objective optimization tasks. It initiates with a pre-defined set of a population of several individuals, each represented by a chromosome that corresponds to a potential optimization solution. GA leverages crossover and mutation operations to generate diverse solutions and uses selection operations to retain the fittest individuals. The process is repeated until a workable solution is found or a termination condition is satisfied.

To address the challenges of operating a grid-connected AC microgrid, we have developed and implemented a day-ahead optimal scheduling approach. Our proposed strategy was tested on the University of Moratuwa microgrid(Figure 2), which currently uses its battery storage system only as a backup storage incurring higher operating costs. Our goal was to minimize the overall operational costs by utilizing the resources of the microgrid while maintaining a consistent electricity supply to the loads.

Figure 2 illustrates the components of the grid-connected AC microgrid system of University of Moratuwa. By optimizing the scheduling of the battery energy storage system and loads, we aimed to increase the microgrid's efficiency and reduce its operational costs. To achieve this, the proposed model uses Genetic Algorithm and demand response schedules are also generated alongside the optimal battery dispatch plan in the developed model. LightGBM, a decision tree-based machine learning method [32], is used to predict solar and load profiles and optimize the microgrid scheduling. The impact of battery degradation is also considered, with a simple and practical battery degradation cost estimation model. Through simulation results, we have demonstrated the effectiveness of our proposed approach for the University of Moratuwa microgrid shown in Figure 2.

This research presents an approach to day-ahead scheduling for grid-connected AC microgrids, with a primary focus on minimizing costs and enhancing operational efficiency. Through the integration of Genetic Algorithm and LightGBM for predictive and optimization purposes, our method uniquely addresses the challenges inherent in microgrid management. Tested on the University of Moratuwa microgrid, our approach demonstrates significant operational cost savings. Moreover, our research fills a crucial gap in the literature by incorporating a comprehensive analysis of battery degradation effects into our optimization model, thereby providing a more realistic assessment of microgrid sustainability and

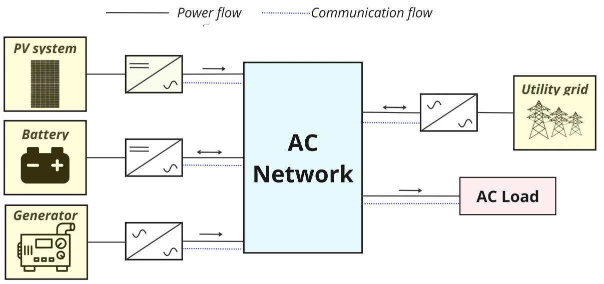

FIGURE 2. Diagram of the main components and connections of the University of Moratuwa Microgrid.

cost management strategies. The novel application of genetic algorithms in microgrid scheduling is a key highlight of our study, introducing tailored chromosome representations, innovative crossover and mutation techniques, and strategic warm restart strategies to enhance solution exploration of the multi-objective optimization problem and efficiency. These advancements underscore the adaptability and efficacy of genetic algorithms in navigating the complex dynamics of microgrid optimization, offering scalable and practical solutions for sustainable energy management.

The remainder of the paper is organized as follows: Section II delves into the impacts of battery degradation on microgrid optimization; Section III provides an overview of the system architecture, including forecasting and optimization frameworks; Section IV discusses mathematical modeling for optimization; Section V outlines the methodology, including forecasting techniques and optimization algorithms; Section VI presents test results and discussions, focusing on data acquisition, forecasting accuracy, and optimization results.

II. BATTERY DEGRADATION IN MICROGRID OPTIMIZATION

Batteries play a crucial role in microgrid systems, revolutionizing energy storage, management, and distribution. They enable efficient energy management by storing excess energy during low-demand or high-renewable generation periods and releasing it during high-demand or limited renewable supply periods. The degradation of Battery Energy Storage Systems (BESS) presents the most serious challenge among the various components of a microgrid due to several reasons:

- The cost of BESS is significant within a microgrid infrastructure, yet its lifespan is comparatively shorter.
- BESS degradation is closely tied to usage patterns. The way batteries are dispatched directly impacts their degradation rate.

While the degradation of other microgrid components such as inverters occurs at a slower pace, their impact is less dependent on usage patterns. Hence, there is no specific advantage in considering the degradation of these components. Therefore, our focus is primarily on BESS degradation, as the monetary cost associated with the degradation of other components is considered insignificant.

The higher replacement costs of batteries significantly influence the economic viability of microgrid systems. An optimal solution for managing a microgrid must, therefore, incorporate strategies to mitigate battery degradation. Battery degradation, significantly influenced by chemical reactions, aging, and charging patterns, presents a critical challenge in microgrid optimization [15], [33].

Research by Koller et al. [15], Zhao [33], Xing [34], and Leonori et al. [26] underlines the importance of integrating degradation costs into battery energy storage system (BESS) management to mitigate operational and replacement costs, which are significant components of microgrid expenses [35].

BESSs, notably Lead-Acid and Lithium-Ion batteries, exhibit finite lifecycles, with operational costs often simplified to constants like the Levelized Cost of Energy (*LCOE*) [35]. Ahsan et al. propose a dynamic model accounting for conversion efficiency and degradation's impact on *SoC*, aiming to reduce microgrid operational costs by up to 12% [35].

This approach not only reduces the need for frequent replacements but also optimizes the overall operational costs of the system, making sustainability and efficiency key factors in microgrid management.

A. BATTERY DEGRADATION FACTORS

Battery degradation significantly affects performance and longevity, influenced by factors like temperature, depth of discharge (DoD), state of charge (SoC), and charge/discharge rates measured as C-rate ((1)). High temperatures and extreme SoC levels accelerate degradation, while high DoD and c-rates cause structural and chemical stress, reducing battery life. Optimizing these factors through thermal management, maintaining moderate SoC levels, and minimizing high c-rates can extend battery lifespan, crucial for efficient microgrid operation. [33].

$$\text{C-rate} = \frac{\text{Charging/Discharging Current (in amperes)}}{\text{Battery Capacity (in ampere-hours)}} \tag{1}$$

1) IMPACT OF TEMPERATURE ON BATTERY DEGRADATION

Temperature significantly influences battery degradation, with high temperatures speeding up the chemical reactions inside batteries, thereby reducing their capacity and lifespan. This acceleration in degradation is due to faster chemical reactions and increased self-discharge rates at elevated temperatures, which can also lead to thermal runaway, posing risks of failure or combustion [36], [37].

Conversely, low temperatures impair battery power delivery, voltage, and capacity, until the temperature rises. Different batteries have optimal temperature ranges, with lithium-ion batteries being particularly sensitive to high temperatures, and lead-acid batteries exhibiting more tolerance [36].

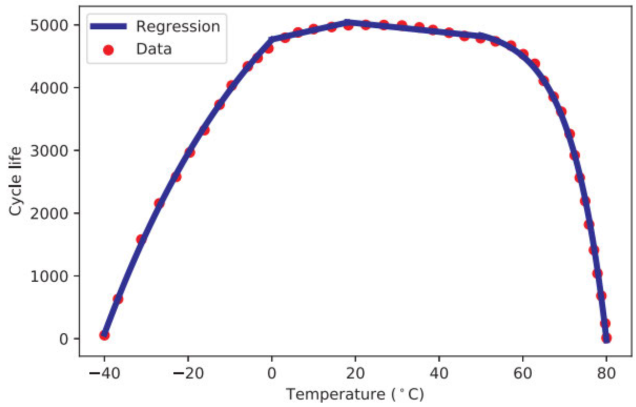

FIGURE 3. Effect of temperature on Li-ion battery cycle-life at 50% DOD [36].

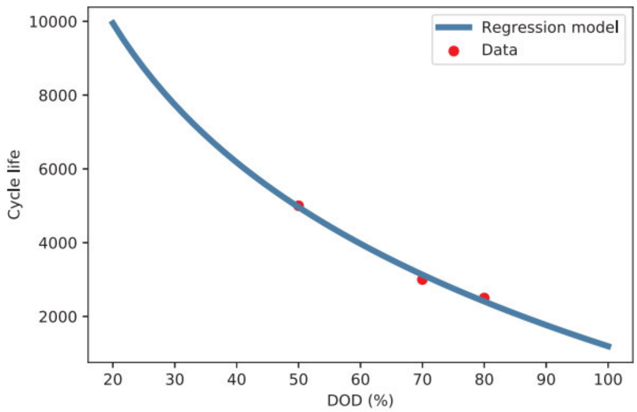

FIGURE 4. Regression curve of Li-ion battery cycle-life vs DOD [36].

However, temperature's impact on battery performance can be effectively managed in microgrids through robust climate control systems, including heat sinks, thermal insulation, and active cooling, to maintain optimal conditions and mitigate degradation [35]. According to Figure 3, the temperature dependence of battery life is less in normal operating temperatures. By adhering to recommended temperature ranges and using advanced thermal management, the negative effects of temperature on batteries can be minimized, making it a less critical factor for degradation in controlled environments.

2) DEPTH OF DISCHARGE (DOD) AND ITS EFFECTS

Depth of discharge (DOD) plays a crucial role in battery degradation, indicating the percentage of energy used from a battery relative to its total capacity [35]. A higher DOD means the battery has been more deeply discharged, which intensifies chemical and structural stresses during charge and discharge cycles, accelerating degradation.

A logarithmic relationship between cyclelife and DoD is obtained for a Li-ion battery in [36] and the relationship is given in (2). α and β are regression coefficients representing the relationship of DoD and cyclelife of a particular battery. BESS manufacturer datasheets [38] provide this relationship and the data is used to estimate the regression coefficients.

$$\text{Cycle Life} = \alpha \cdot \log(\text{DoD}) + \beta \tag{2}$$

The Figure 4 illustrates this logarithmic relationship and cycle life of Lithium-ion batteries decreases as the DOD of charging cycles increases [36]. This relationship is crucial for understanding how to optimize battery usage to extend its lifespan. High DOD levels can cause electrode damage, electrolyte breakdown, and mechanical stress, which diminish capacity and cause physical degradation. Conversely, maintaining batteries within recommended DOD limits can reduce stress and enhance longevity, underscoring the importance of managing DOD to mitigate its effects on battery health.

3) STATE OF CHARGE (SOC) AND ITS ROLE IN DEGRADATION

The State of Charge (SOC) is a key factor in battery health, representing the current energy level as a percentage of its full capacity. Extreme SOC levels, either very high near 100% or very low close to 0%, significantly contribute to battery degradation. At high SOC, stress on internal components increases, leading to enhanced chemical activity and elevated temperatures, which harm battery performance. Conversely, low SOC strains the battery's active materials, shortening its lifespan. To minimize degradation, it's advised to keep the SOC between 20% and 80%. Effective battery management systems and charging strategies are essential for maintaining optimal SOC ranges, thus extending battery durability and efficiency.

4) CHARGE AND DISCHARGE RATES (C-RATE) AND THEIR INFLUENCE

Charge and discharge rates, known as c-rates, critically affect battery degradation. The c-rate measures how quickly a battery is charged or discharged in comparison to its total capacity. Charging or discharging at high c-rates puts the battery under significant stress, leading to more heat production. This increase in temperature speeds up chemical reactions within the battery, causing a quicker degradation of its active materials and reducing its overall lifespan. High c-rates can also inflict mechanical and structural damage, exacerbating degradation.

Conversely, employing slower charge and discharge rates can alleviate stress on the battery. It helps in minimizing heat production and slowing down chemical reactions, which aids in reducing degradation and prolonging the battery's lifespan.

B. BATTERY DEGRADATION MODEL

BESS manufacturers typically estimate the number of operational cycles under specific charging and discharging conditions before the BESS undergoes degradation and can only retain 70-80 % of its original energy capacity [38]. However, various factors like temperature, state of charge (SoC)/depth of discharge (DoD), and charging and discharging current/power can accelerate the degradation of BESS and reduce its lifespan. [15].

The state of charge (SoC) refers to the amount of remaining capacity within a battery relative to its fully charged state. It is typically expressed as a percentage, where 100% indicates a fully charged battery and 0% indicates a fully discharged battery. Depth of discharge (DoD) measures the extent to which a battery's capacity has been utilized during a single discharge cycle, expressed as a percentage of its total capacity [36]. For instance, a battery at to 60% DoD if full capacity means that the SOC is 40%. SoC or DoD are very useful for measuring the usage patterns of a BESS. If the battery is frequently discharged to higher depths (higher DoDs), its lifespan will reduce.

Since Battery Energy Storage Systems (BESSs) often come with robust climate management mechanisms, the impact of elevated operational temperatures on aging is frequently ignored [36]. Depth of Discharge (DoD) emerges as a paramount factor influencing battery degradation [35]. Thus, a Battery Degradation Cost (BDC) model that incorporates DoD for estimating the lifespan in terms of cycle life is proposed.

According to the specifications released by manufacturers of Li-ion batteries [38], the rate of battery degradation does not depend on the charging or discharging rates provided that the c-rate remains below 1 [39]. Therefore, the influence of charge and discharge rates on the cycle life of the battery is considered negligible at low charging speeds, which is a factor excluded from this study.

The formula for calculating this phenomenon, as presented in [35], employs the equation proposed by Ahsan et al. [35] to determine the variation in the state of health(ΔSOH) based on the state of charge levels and depth of discharge of BESS. The temperature dependence is neglected in this equation because the BESS has a strong climate control system, and SoC and DoD have an inverse relationship.

$$\begin{aligned}\Delta\mathrm{SOH}(Q_{t0}, Q_{t1}, I) &= \Delta\mathrm{SOH}(Q^{\mathrm{MAX}}, Q_{t1}, I)\\ &\quad - \quad \Delta\mathrm{SOH}(Q^{\mathrm{MAX}}, Q_{t0}, I)\\ &= \frac{1}{N_{\mathrm{cycle}}(Q_{t1}, I)} - \frac{1}{N_{\mathrm{cycle}}(Q_{t0}, I)} \end{aligned} \tag{3}$$

The financial cost associated with battery degradation is then calculated by taking into account the initial investment in the BESS and the overall change in the battery's health.

III. SYSTEM OVERVIEW

This section introduces the system architecture of the model, detailing system architecture, forecasting mechanisms, and the optimization challenge it addresses to enhance energy efficiency and cost-effectiveness.

A. SYSTEM ARCHITECTURE

The proposed model is designed for the University of Moratuwa microgrid, which is connected to the grid. It incorporates photovoltaic (PV) units for generating solar energy, a Battery Energy Storage System (BESS) for managing supply and demand, and buildings that are the primary consumers of energy. The system is augmented by Distributed Energy Resources (DERs), such as backup power generators.

It collects data on power generation, consumption, and weather at five-minute intervals, which is used to predict daily energy requirements and production. This forecasted data informs an optimization process that determines the optimal schedule for battery dispatch and demand response strategies, aiming to minimize costs.

B. LOAD AND POWER GENERATION FORECASTING

The microgrid optimization problem is heavily reliant on precise forecasting of solar power generation and building power consumption. This forecasting process involves the analysis of pre-processed data on solar power generation and building power consumption to identify patterns, trends, and seasonal variations.

Through experimentation, the optimal set of input features for each forecasting model is determined. Figure 5 presents the overall project model diagram, integrating these forecasting outputs into the optimization problem.

C. OPTIMIZATION PROBLEM

The optimization problem aims to determine two outcomes: (1) optimal battery dispatch schedule and (2) a Demand Response(DR) strategy for the microgrid while adhering to various constraints such as maximum charging and discharging rates, and allowable state of charge range.

The scheduling problem for the BESS is modeled as a series of discrete charging and discharging rates (X^1) across time intervals within a day, with rates varying from maximum discharge to maximum charge. Additionally, the demand response (DR) strategy encompasses shifting Type I flexible loads within specified time frames to optimize start times (X^2) and shedding Type II flexible loads to balance supply-demand and minimize costs, represented by binary values indicating load curtailment (X^3). This comprehensive approach integrates BESS dispatch, load shifting, and shedding strategies to minimize operating costs while considering consumer comfort and energy supply-demand balance.

IV. MATHEMATICAL MODELING

The following section outlines the comprehensive mathematical modelling framework employed to optimize the operation of a Battery Energy Storage System (BESS) and to develop an effective Demand Response (DR) strategy within a microgrid context. This modelling approach aims to balance energy supply and demand efficiently, minimize operational costs, and maintain system reliability and consumer comfort.

A. PROBLEM DEFINITION

The objective of this study is to optimize the use of the BESS and to develop an effective DR strategy for a microgrid. This involves creating a schedule for when and how the BESS

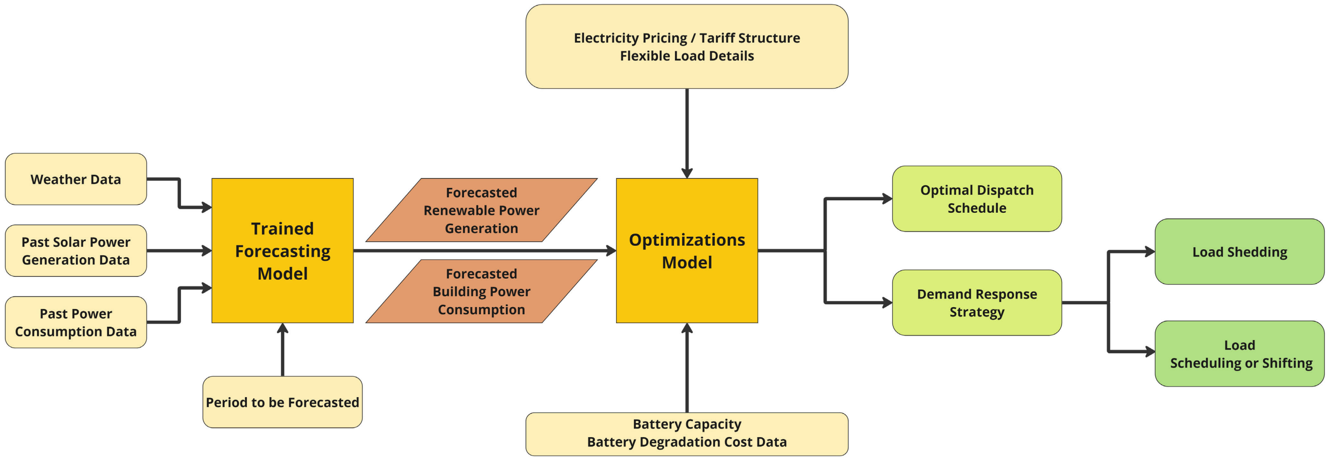

FIGURE 5. Proposed Model Diagram depicting the use of forecasting model output as inputs for optimization model, alongside other optimization input parameters.

should charge or discharge throughout the day. We represent this schedule with X^1, a sequence of T numbers, where T is the number of time slots in a day. Each number, c_t, indicates whether the BESS is charging (positive value), discharging (negative value), or idle (zero) at time slot t, within a range from $-c_{max}$ to $+c_{max}$. For example, in our BESS schedule shown in Figure 10, the numbers 3 to -3 represent different rates of charging or discharging.

The strategy for Demand Response (DR) integrates two pivotal components: (1) shifting Type I flexible loads and (2) shedding Type II flexible loads. Type I flexible loads have an allowable time period (starting time t_s, terminating time t_e), power consumption, and duration t_d. These loads can be shifted within the allowable time period to minimize total operating costs. For an input case of m_1 Type I flexible loads, the DR strategy for Type I loads is represented by X^2, a series of M_1 length representing the starting time (hour of the day, $h_i \in [0, T-1]$ where $i \in [0, M_1]$) of each Type I flexible load according to a given schedule. The DR strategy for Type I load schedule in Figure 10 depicts the start time for each load.

Type II flexible loads are defined as electric loads that can be turned off to balance the supply-demand and minimize costs. However, this demand response (DR) method, also called load shedding, affects consumer comfort. The loads that can be shed are represented by a series of M_2 numbers, and they have corresponding penalty values (p_i for $I \in [1, M_2]$) representing consumer discomfort. The DR strategy for Type II flexible loads is represented by X^3, a series of M_2 binary values, as shown in Figure 10. Each element $b_i \in [0, 1]$ in X^2 indicates curtailed loads. In Figure 10, curtailed loads are represented by 1, and unaffected loads are represented by 0.

B. OBJECTIVE FUNCTION

The objective function encapsulates the daily operational cost associated with the AC microgrid, encompassing electricity costs, expenses due to battery wear, and penalties associated with demand response (DR). Initially, we introduce the concept of the net load (P_{net}), calculated as the difference between power consumption by the building (P_C) and the power produced by solar panels (P_G), as depicted in (4)

$$P_{\text{net}} = P_C - P_G \tag{4}$$

A microgrid system typically incurs operational costs such as electricity charges for energy exchange with the main grid and the cost of fuel for dispatchable energy sources utilized within the microgrid [40]. In the case of a fully renewable energy microgrid, fuel costs are nonexistent. However, despite being less apparent, the depreciation or degradation of system components constitutes a significant operational cost. While the degradation-related costs of renewable energy sources, inverters, and other equipment tend to be minimal, the focus often centers on the cost of battery degradation. Additionally, certain demand response methods, like load shedding, can lead to consumer discomfort, prompting the incorporation of penalties into models to account for such discomfort [41]. These penalties help quantify the impact of consumer discomfort on the overall operational cost of the microgrid system.

The total cost for a given day d, denoted by C_d, is a sum of the electricity cost $E(X_d^1)$, battery degradation cost $B(X_d^1)$, and DR penalties $P(X_d^3)$. Equation (5) demonstrates that the electricity cost $E(X_d^1)$ depends on the net load $P_{\text{net},d}$, and the operational decisions X_d^1, X_d^2, and X_d^3, whereas the cost of battery degradation is a function of X_d^1 and the DR penalty is determined by the DR strategy for type II loads X_d^3 for the day d.

$$\min_{X_d^1, X_d^2, X_d^3} C_d = E(P_{\text{net},d}, X_d^1, X_d^2, X_d^3) + B(X_d^1) + P(X_d^3) \tag{5}$$

1) COST OF ELECTRICITY

The cost of electricity is calculated based on the time-varying electricity prices, represented by $\pi_t$fort $\in [0, T]$. The cost of electricity also depends on the total electric load supplied to the microgrid by the main grid utility provider. The total electric load is the sum of P^t_{net}, flexible load electricity consumption at time t, P^t_S battery charging or discharging rate at time t, P_{BESS} as shown in Eq. (6).

$$E = \sum_{t=1}^{T} \pi^t \cdot (P^t_{net} + P^t_{BESS} + P^t_S) \tag{6}$$

Assuming constant Direct Current (DC) voltages, the charging or discharging power of the BESS $P^t_{BESS} \in [-P^{max}_{BESS}, -P^{max}_{BESS}]$ is proportional to c_t, the discrete representation of charging rates.

2) BATTERY DEGRADATION COST

The equation used to model this effect is mentioned in [35], The Eq. (3) proposed by Ahsan, et.al [35] is employed to find the change in the state of health(ΔSOH) based on the state of charge levels and depth of discharge of BESS.

$$\begin{aligned} \Delta\mathrm{SOH}(Q_{t0}, Q_{t1}, I) &= \Delta\mathrm{SOH}(Q^{\mathrm{MAX}}, Q_{t1}, I) \\ &\quad - \Delta\mathrm{SOH}(Q^{\mathrm{MAX}}, Q_{t0}, I) \\ &= \frac{1}{N_{\mathrm{cycle}}(Q_{t1}, I)} - \frac{1}{N_{\mathrm{cycle}}(Q_{t0}, I)} \end{aligned} \tag{7}$$

The financial cost associated with battery degradation is then calculated by taking into account the initial investment in the BESS and the overall change in the battery's state of health

3) DEMAND RESPONSE PENALTY

Demand Response (DR) penalties are assigned on type II flexible loads subject to curtailment under the type II loads DR strategy. These penalties, denoted as P_i for each i within the set $\{1, \ldots, M_2 - 1\}$, quantify the discomfort experienced by consumers due to the reduction in load. The formula defining these penalties is presented in Eq. (8).

$$P(X^3_d) = \sum_{i=1}^{M_2} b_i \cdot P_i \tag{8}$$

C. CONSTRAINTS

This section outlines the constraints related to operation within the microgrid system. Specifically, we define limits on the battery's charging rate to prevent charging at a rate exceeding its design capabilities. Additionally, we introduce state of charge (SOC) constraints to maintain the battery's charge within optimal levels, thus avoiding the risks of overcharging or deep discharging, both of which could degrade the battery's performance and lifespan. Unlike the constraints for battery charging and SOC, the constraints related to the power transfer capacity of distribution lines are omitted, assuming their maximum transfer capability always surpasses the actual demands of power supply. Furthermore, it is essential to ensure that the battery's charge level at the conclusion of the operational period reverts to its initial state,

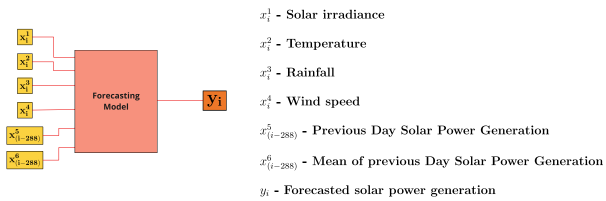

FIGURE 6. Solar forecasting model.

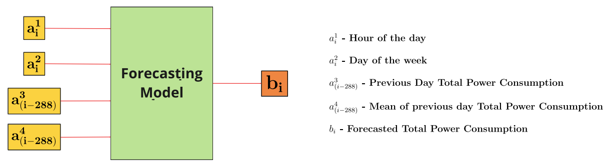

FIGURE 7. Building load forecasting model.

necessitating that the cumulative charging activity over the designated T periods results in a net zero change. These operational constraints are detailed in Equations (9), (10), and (11).

$$-P^{max}_{BESS} \leq P^t_{BESS} \leq P^{max}_{BESS} \tag{9}$$

$$SOC^{min}_{BESS} \leq SOC^t_{BESS} \leq SOC^{max}_{BESS} \tag{10}$$

$$\sum_{0}^{T} c_t = 0 \tag{11}$$

In addition, during scheduled power interruptions the net power exchange between main grid and microgrid is zero. Given T_1 as the starting time and T_2 as the ending time of a scheduled power interruption, the relationship between the net power (P^t_{net}), battery energy storage system power (P^t_{BESS}), and solar power generation (P^t_S) within the interval $T_1 < t < T_2$ is represented by Equation 12

$$P^t_{\mathrm{net}} + P^t_{\mathrm{BESS}} + P^t_S = 0, \quad \text{for } T_1 < t < T_2 \tag{12}$$

V. METHODOLOGY

A. SOLAR POWER AND BUILDING LOAD FORECASTING

The microgrid optimization problem depends on the accurate forecasting of solar power generation and building power consumption. A sophisticated algorithm that considers the variations and dependencies of numerous variables, including the time of day, the weather, and load-consuming activities, is needed to achieve this.

The pre-processed solar power generation and building power consumption data is examined to find patterns, trends, and seasonal fluctuations prior to train the forecasting models. The input variables for solar power generation forecasting include weather data, solar irradiation, ambient temperature, rainfall and past day's solar power generation data. For building power consumption forecasting, the input variables include schedule variables such as the hour of day, day of week, and previous load consumption data. In addition the ambient temperature was used as another input variable to further improve the accuracy.

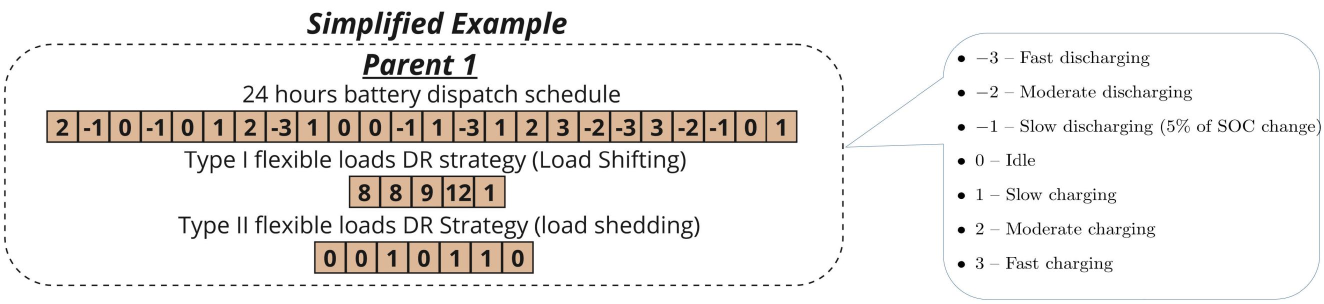

FIGURE 8. Example-Chromosome representation in the genetic algorithm.

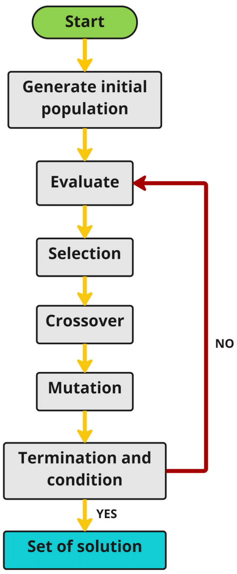

FIGURE 9. Flow chart of genetic algorithm: The selection crossover and mutation operations.

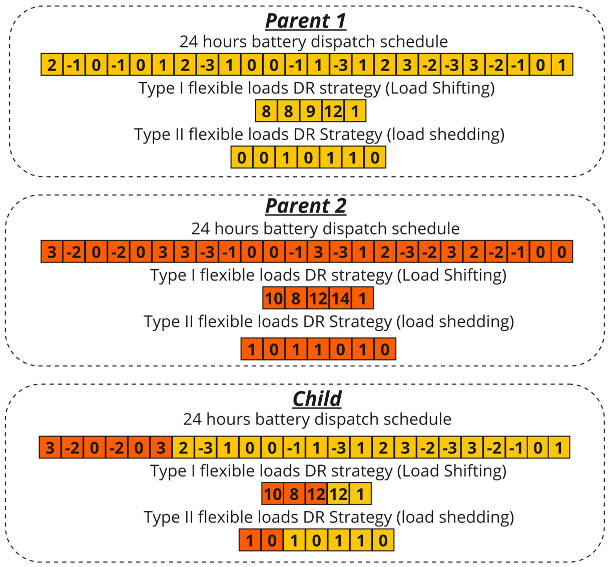

FIGURE 10. Example-Triplet crossover function (I) for chromosomes.

LightGBM, a machine learning-based forecasting library that uses boosting techniques to increase speed, is used to carry out the forecasting. With its innovative gradient-based one-side sampling algorithm, LightGBM can successfully handle large datasets. Through experimentation, the ideal set of input features for each building and load forecasting model is chosen. The Figure 6 shows the inputs of Solar Forecasting model and Figure 7 shows the inputs of Building Load Forecasting model. The Figure 5 shows complete model diagram of the project.

B. OPTIMIZATION ALGORITHM

1) CHROMOSOME REPRESENTATION

The scheduling for the Battery Energy Storage System (BESS) and Demand Response (DR) strategies, encapsulating charging/discharging rates and load management, is optimized using a genetic algorithm. This approach addresses operational constraints and balances supply-demand.

2) GENETIC ALGORITHM

The genetic algorithm (GA) stands as a broadly applied, adaptive algorithm based on a population approach, renowned for its flexibility and efficiency in optimization tasks. It begins with an initially determined population comprising numerous entities, each symbolized by a chromosome, which signifies a possible solution for optimization. GA employs crossover and mutation techniques to cultivate a variety of solutions and applies selection techniques to preserve the most suitable individuals. This procedure is iterated until a viable solution emerges or a predefined termination criterion is met. The operational schema of the genetic algorithm is depicted in the Figure 9 [42].

Each chromosome is a triplet of three series, BESS dispatch schedule X^1, type I flexible load DR strategy X^2, and type II flexible load DR strategy X^2. X^1 is a series of T integers each representing the discrete charging or discharging rate c_t at time period t.

The second and third series represent the DR strategy of flexible load type I X^2 and DR strategy flexible load type II X^2. An example chromosome is shown in Figure 8 and Figure 10

3) INITIALIZING POPULATION

The effectiveness and speed at which genetic algorithms (GAs) converge towards optimal fitness values are significantly affected by the composition of the initial population. For superior results, the initial population is generated randomly, adhering to a uniform distribution.

The chromosome series X^1 is generated randomly from T integers in the range $[-c_{max}, +c_{max}]$, X^2 is generated randomly from M_1 integers in the range $[0, T_e - T_d]$ where T_e and T_d are the termination time land duration of type I flexible load. X^2 is generated randomly from M_2 binary integers in the range [0, 1].

4) SELECTION

In the selection phase of a genetic algorithm, a probability distribution is created based on the fitness of individuals, assigning higher probabilities to fitter individuals. These probabilities are normalized to ensure their sum equals 1, and then cumulatively summed to form a distribution list. This setup facilitates stochastic selection, where a random value between 0 and 1 is used to select an individual, favoring those with higher fitness. This method biases the selection process towards fitter individuals, enhancing the algorithm's ability to evolve better solutions over time.

5) FITNESS FUNCTION

Parents are selected based on the fitness of the creatures in the population, with higher probabilities of selection given to the fittest creatures based on a fitness function that assesses the quality of each solution, the genetic algorithm generates new solutions attractively using selection, crossover, and mutation operations. The fitness function is defined as awarding higher fitness scores to solutions with lower operating costs.

When the operating cost of a schedule is f, the fitness is calculated in an inverse relationship as shown in equation (13). Here $min(f)$ is the minimum value of cost of all schedules generated so far.

$$f(x) = \frac{1}{(\max\{SN, f - \min(f)\})^k} \tag{13}$$

The k is chosen based on experiments to maximize the training efficiency. We found $k = 0.25$ as a good fit. SN is a small number which is used in the denominator to prevent division by zero when $f = min(f)$.

6) CROSSOVER OPERATION

The Crossover function is the most important operation in genetic algorithm [43]. A single point crossover function is defined to crossover a triplet of three chromosomes separately as shown in Figure 10 [1].

In the crossover process, there's a risk that key characteristics of a specific chromosome series might be lost due to the deficiencies present in another series within the same chromosome. To mitigate this issue, an alternative crossover method is introduced in this paper, as illustrated in the Figure 11, which focuses on crossing over one series at a time. By selecting a series randomly, this approach enhances the results while making convergence speed faster than the convergence speed observed with chromosome structure I.

7) WARM RESTART

One of the key challenges in genetic algorithms is observed when the entire population becomes dominated by a certain chromosome, which represents a local minimum rather than a global minimum. Although mutation is employed to prevent the population from getting stuck in a local minimum, sometimes it is not sufficient.

Warm restart in genetic algorithms refers to a technique where the algorithm is restarted from a state that is not the initial random state, but rather from a partially evolved state or solution. This approach leverages the knowledge gained from previous runs of the algorithm to potentially accelerate convergence towards an optimal or near-optimal solution. By initializing the population with individuals (solutions) that have already shown promise, rather than starting from scratch, the genetic algorithm can explore the solution space more efficiently. This method helps in avoiding redundant exploration of less promising regions of the solution space, thereby saving computational resources and time. Warm restarts are particularly useful in dynamic optimization problems where the solution landscape changes over time or when fine-tuning a solution to a highly complex problem.

8) CONSTRAINT MANAGEMENT

To manage constraints in genetic algorithms, two methods can be employed: penalizing chromosomes that violate the constraints or filtering out chromosomes that satisfy the constraints and advancing them to the next population. Drawing inspiration from natural selection, where creatures that do not meet minimum survival requirements fail to survive, we adopted the second method. Consequently, we eliminated chromosomes that do not satisfy the constraints.

VI. TEST RESULTS AND DISCUSSION

A. DATA ACQUISITION

The data used in this study was obtained from the Microgrid laboratory of the University of Moratuwa. The collected data includes solar power generation and building power consumption data from four different buildings for a period of four months from November 2022 to February 2023.The building power consumption and solar power generation of these four buildings were aggregated for analysis. Additionally, weather data such as solar irradiance, temperature, rainfall, and wind speed collected at the university premises during the same period was obtained. The collected data was pre-processed, cleaned, and formatted before being fed into the forecasting algorithm.

In addition to electricity prices, forecasted solar power generation, and building power consumption data, the optimization problem requires a few other inputs to generate an optimal demand response strategy, including the power consumption and flexibility of certain loads. These loads are defined as flexible loads. As demand response methods such as load shifting and curtailing can affect day-to-day activities and consumer comfort, a survey is conducted to assess them.

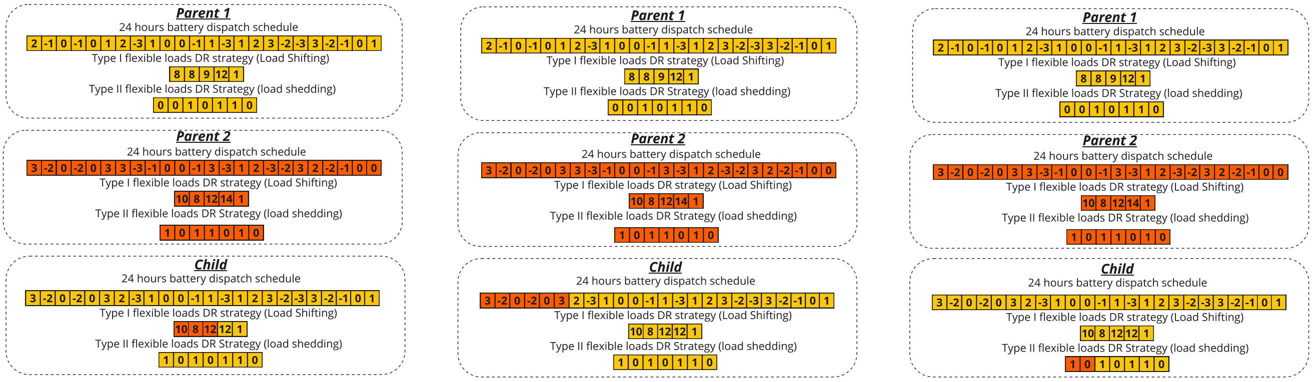

FIGURE 11. **Example-Crossover function (II) for chromosomes.**

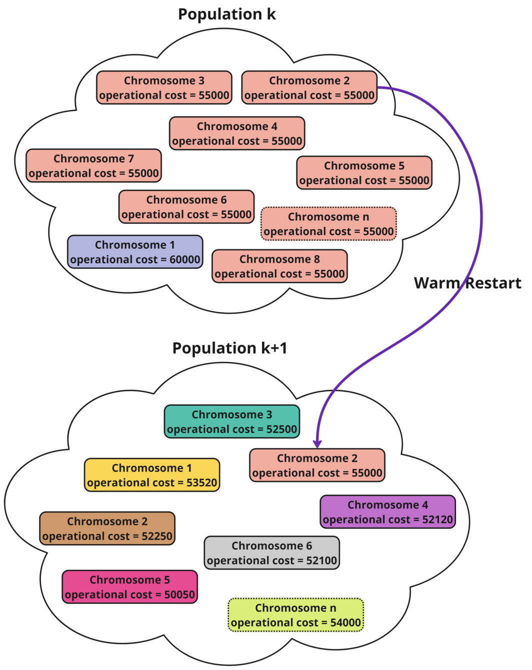

FIGURE 12. **Illustration of warm restart.**

One of the non-essential loads in the context of the Microgrid considered for this project is the air conditioners in some lecture rooms. A survey conducted among students at the University of Moratuwa provided insights into the perceived importance of air conditioning, aiding in the estimation of discomfort penalties and suggesting a methodology for broader application in microgrid load management.

B. SOLAR GENERATION FORECASTING

The solar power generation forecasting model was developed with a learning rate of 0.075, aimed at predicting day-ahead solar power generation with hourly intervals. This model's performance was assessed by comparing the forecasted solar power generation against the actual solar power generation data. The assessment yielded an R^2 score of 0.91, indicating a high level of accuracy in the forecasts produced by the model.

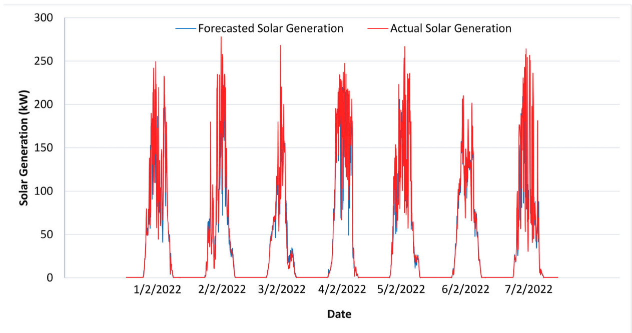

FIGURE 13. **Solar generation forecasting.**

This score suggests that the model is capable of capturing a significant portion of the variance in solar power generation. The forecasting results for the first week of February, as compared to the actual solar power generation, are depicted in Figure 13. The high R^2 score demonstrates the model's effectiveness in predicting solar power generation, making it a valuable tool for energy management and planning in solar energy-dependent applications.

We simulated and analysed with different forecasting models for Solar Generation Forecasting, and their respective performances are shown in Table 1. Among them, LightGBM has the second-highest accuracy. Considering its faster training speed, it is the best choice.

C. LOAD CONSUMPTION FORECASTING

For the building load forecasting, the model was also trained with a learning rate of 0.075. This model forecasts the building load consumption a day ahead, with predictions made for each hour. The accuracy of the building load forecasting model was evaluated by comparing its predictions against the actual load consumption, achieving an R^2 score of 0.93. This indicates an excellent predictive performance, showing that the model can accurately forecast building load consumption with minimal error. The forecasting results for the first week of February, in comparison with the actual building load consumption, are illustrated in Figure 14.

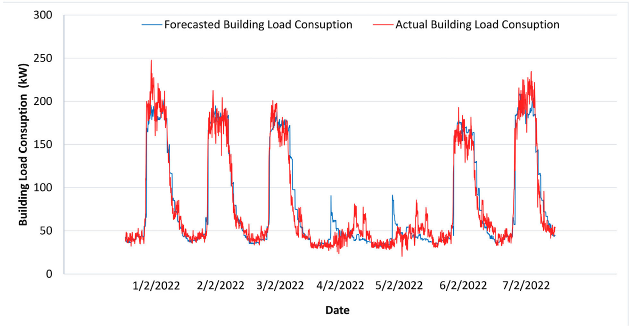

FIGURE 14. Load consumption forecasting.

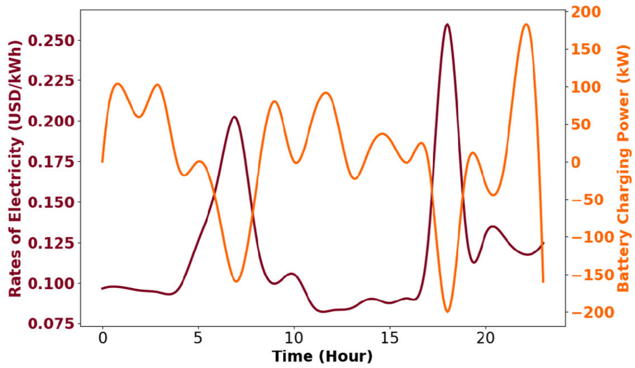

FIGURE 15. Battery dispatch plan based on price variation.

The high R^2 score underlines the model's efficiency in understanding and predicting the consumption patterns of the building load, thereby facilitating more effective energy management and optimization strategies.

We experimented with different forecasting models for Solar Generation Forecasting, and their respective performances are shown in Table 1. In terms of solar forecasting accuracy, LightGBM achieves an R2 score of 0.90, placing it closely behind Random Forest's 0.91. Additionally, LightGBM demonstrates robust performance for load forecasting with an R2 score of 0.93, which is only slightly lower than Recurrent Neural Networks' impressive 0.97. Notably, LightGBM's training speed surpasses that of its counterparts, making it a practical and efficient solution for forecasting tasks. Therefore, considering its balanced performance and expedited training process, LightGBM emerges as the optimal choice for accurate and efficient solar generation and load forecasting.

The validation of LightGBM results further underscores its reliability and suitability for forecasting applications. During testing the optimization model which produced an optimal schedule based on forecasted results performed well with actual data without violating any constraints. Extensive validation procedures, including cross-validation and testing on independent datasets, confirm the consistency and generalizability of LightGBM's predictive capabilities. Therefore, the comprehensive validation of LightGBM results reinforces its status as a dependable and effective forecasting tool, empowering stakeholders to optimize resource allocation and enhance operational efficiency in renewable energy systems.

D. OPTIMIZATION RESULTS

1) OPTIMIZATION CONVERGENCE

In this study, the genetic algorithm-based optimization model was applied to generate day-ahead hourly battery dispatch schedules for the month of February, considering forecasted solar power generation and consumption patterns. The model initiated with a set of 1000 potential schedules, undergoing 50 iterations within the genetic algorithm framework. The evolution of electricity costs over these iterations is illustrated in Figure 17. The model was configured with 10 distinct battery charging states, adhering to a maximum charge and discharge rate of 0.5C. Our evaluation involved comparing the cost implications under the existing Time-of-Use (TOU) tariff regime in Sri Lanka, as detailed in Table 2. According to the current electricity tariff structure in Sri Lanka, the proposed model facilitated a reduction in electricity expenses by 13.86% on a monthly basis. Nevertheless, when considering the impact of battery degradation costs, the net savings in total operating expenses were marginal in relation to the prevailing tariff scheme.

Amidst the ongoing reforms within the Sri Lankan power sector, there is an anticipation of the introduction of more reflective time-varying electricity pricing structures or a real-time electricity market in the near future. In light of these potential changes, our study extended the applicability of the optimization model by incorporating electricity market prices. We used time varying electricity market prices from Victoria, Australia for the period of February 2023, as reported by the Australian Energy Market Operator (AEMO) on their National Electricity Market (NEM) dashboard [44]. Our microgrid optimization model, when tested under time varying prices in these market conditions, showcased a significant reduction in monthly electricity costs by 39.42%, alongside a noteworthy decrease in total monthly operating costs(considering battery degradation) by 9.52%. This pronounced cost reduction shows the critical role of microgrid optimization in environments characterized by greater price volatility within electricity markets. The findings suggest that, as electricity pricing structures evolve to more closely reflect real-time market conditions, the potential for savings through optimized microgrid management becomes increasingly substantial, thereby highlighting the importance of adopting advanced optimization techniques in anticipation of future market dynamics.

One of the primary factors contributing to the cost reduction in the Australian Energy Market is the implementation of an optimal battery dispatch schedule. This strategy becomes particularly effective when there is a significant variation in prices, allowing for the charging of batteries during periods of low prices and discharging them when prices are high. This approach can result in considerable savings, as demonstrated in the Figure 15.

TABLE 1. Forecasting model performance.

Model	R2 Score (Solar Forecasting)	R2 Score (Load Forecasting)
Random Forest (RF)	0.91	0.90
Artificial Neural Networks (ANNs)	0.89	0.8
Recurrent Neural Networks (RNNs)	0.78	0.97
LightGBM	0.90	0.93

TABLE 2. Tariff structure for government facilities: An overview of CEB pricing(February 2023).

Time slots	Energy Charge (Rs./kWh)
Day (05:30 - 18:30 hrs)	47.00
Peak (18:30 - 22:30 hrs)	55.00
Off Peak (22:30 - 05:30 hrs)	39.00
Demand Charge (Rs./kVA) - 1600.00	
Fixed Charge (Rs./Month) - 5000.00	

TABLE 3. Comparison of monthly electricity costs.

	Optimal Schedule	Current Schedule	Reduction Rate
Electricity Cost in Sri Lanka Tariff Structure (LKR)	1,067,100	1,244,000	14.22%
Total Operation Cost in Victoria, Australia Electricity Market Price (AUD)	1,643.28	1,816.26	9.52%

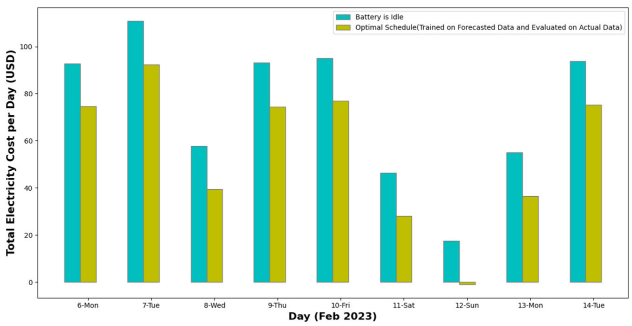

FIGURE 16. Operational cost reduction compared to idle battery state.

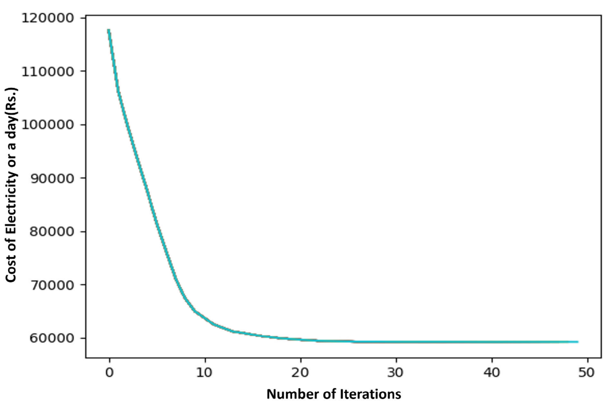

FIGURE 17. Genetic algorithm training-daily electricity cost (Rs.) vs number of iterations.

VII. CONCLUSION

In conclusion, our study demonstrates the potent synergy of Genetic Algorithms and LightGBM in optimizing the operational efficiency of AC microgrids. Through intelligent demand response strategies and precise forecasting of solar power generation and load consumption, we achieved a significant reduction in operational costs by 14.22% under Sri Lanka's current tariff structure. This underscores the transformative potential of advanced scheduling and proactive demand response management in enhancing microgrid sustainability and efficiency. Moreover, by incorporating battery degradation costs into our model, we contribute to the discourse on sustainable energy management, emphasizing the extension of battery lifespan.

The successful application of our model within the University of Moratuwa microgrid validates the efficacy of integrating machine learning techniques with optimization algorithms to refine microgrid operations. This research not only paves the way for scalable solutions to reduce electricity costs and improve system reliability but also establishes a foundation for future studies to explore the integration of additional renewable energy sources, sophisticated forecasting models, and real-time optimization strategies.

Given the dynamic nature of energy markets and the intermittent characteristics of renewable energy sources, our findings offer valuable insights into microgrid optimization. Future endeavors may expand the model to include real-time data analytics, examine the impact of electric vehicles on microgrid dynamics, and apply our approach to larger, more complex energy systems. This would further validate its effectiveness and adaptability, marking a significant step toward realizing the full potential of microgrids in the transition to sustainable energy systems.

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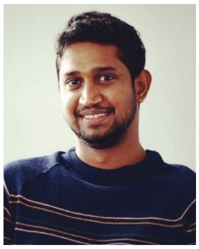

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