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A battery degradation-aware energy management system for agricultural microgrids

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ABSTRACT

The integration of renewable energy sources (RESs) into power grids underscores the necessity for efficient energy storage solutions to ensure power balance and increase grid reliability. Although battery energy storage systems (BESSs) are pivotal for storing excess energy from RESs and mitigating peak demand periods, their chemical nature poses limitations, particularly in microgrid (MG) applications, due to degradation concerns that can lead to reduced performance over time. This necessitates careful consideration of degradation effects in optimizing system design and operation. This paper addresses this issue through developing a novel methodology aimed at optimizing the operation of renewable-based MGs while accounting for the degradation mechanisms of the battery storage systems. A machine learning model based on the XGBoost strategy is developed to predict the remaining useful life (RUL) of Lithium-ion (Li-ion) batteries, leveraging initial battery characteristics. This data-driven model is then incorporated into the day-ahead scheduling problem of an agricultural MG as a use-case to assess the impact of battery degradation modeling on the MG operation in both grid-connected and island operation modes. The proposed methodology utilizes the Coati Optimization Approach (COA) to determine optimal battery charging and discharging policy related to battery cycle limitations. The Monte Carlo Simulation (MCS) approach is employed to generate different scenarios reflecting varying power generation from RESs, electricity price volatility, and load demand variations. Case studies conducted on a real-world agricultural MG in Ankara, Turkey, demonstrate the effectiveness of the proposed methodology in reducing the total MG costs including both operational and degradation costs. Sensitivity analyses underscore the robustness of the methodology across various RES penetration levels and market conditions. Results reveal a reduction of 55.30% and 41.23% in the degradation cost of the agricultural MG in grid-connected and island modes, respectively, through the integration of the proposed data-driven-based battery degradation modeling.

1. Introduction

In the evolving landscape of RESs, the development of MGs emerges as a pivotal factor in shaping the future smart power systems [1]. As RESs continue to gain prominence, their contribution to power generation experiences remarkable growth, reshaping the dynamics of energy systems. Nevertheless, the inherent stochastic and intermittent nature of RESs poses significant challenges to system stability and availability [2]. To address these uncertainties, BESSs emerge as a compelling solution, providing the necessary flexibility to manage the variability of RESs' power generation. BESSs can efficiently store excess energy from RESs and inject it into the grid during high-peak demand periods, enhancing grid stability and reliability [3]. Consequently, accurate modeling of BESS becomes paramount in power systems analyses, particularly in sectors such as agriculture where reliable energy supply is crucial for operations.

Agricultural MGs are distinct from conventional MGs due to their unique load profiles, energy usage patterns, and operational requirements. These systems are tailored to meet the fluctuating and seasonal energy demands of agricultural activities, such as irrigation, crop processing, and storage, with peak loads occurring during critical farming periods. Situated in remote or disaster-prone areas, agricultural MGs require a robust and autonomous operation, often including islanding

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Nomenclature	
Indices	
t	Time index
i	Index of controllable generator units
cg	Controllable generator units
ess	Energy storage system index
Parameters	
ΔT	Dispatch time interval [h]
Ψ	Backup power percentage [%]
$EC_{ess}^{\max}/EC_{ess}^{\min}$	Maximum/Minimum energy capacity of BESS [kWh]
$EC_{\mathrm{ess}}^{t_0}/EC_{\mathrm{ess}}^{t_{24}}$	Initial/End energy capacity of BESS [kWh]
$P_{ess,ch}^{\max}/P_{ess,ch}^{\min}$	Maximum/Minimum charging power of BESS [kW]
$P_{ess,dis}^{\max}/P_{ess,dis}^{\min}$	Maximum/Minimum discharging power of BESS [kW]
$P_{ess}^{\max}$	Maximum power of BESS [kW]
$\xi_{ess}^{ch}/\xi_{ess}^{dis}$	Charging/Discharging efficiency of BESS [%]
EP/ES	Electricity purchase/sell price [Lira/kW]
$OP_{cg}^{\min}/OP_{cg}^{\max}$	Maximum/Minimum capacity of controllable generator [kW]
$Th_{\mathrm{grid}}^{\max}$	Maximum thermal constraint on the tie-line connecting the main grid and the microgrid [kW]
$RL_{cg}^{\mathrm{up}}/RL_{cg}^{\mathrm{down}}$	Ramp-up/Ramp-down limitation of controllable generator [kW/h]
C_{cg}	Unit cost of controllable generator power [Lira/kW]
C_{cg}^{nl}	Cost of controllable generator at no load [Lira]
C_{cg}^{su}	Cost of controllable generator at start-up [Lira]
$\kappa_{bn,batt}$	Price of brand-new battery [Lira]
$\kappa_{slvg,batt}$	Price of salvaged battery [Lira]
N	Number of generators
K_1	Battery charge coefficient
K_2	Battery discharge coefficient
Deg-cost	Battery degradation cost for each cycle [Lira]
Deg-rate	Battery degradation rate for each cycle [%/cycle]
Variables	
OP_{cg}	Controllable generator output power [kW]
$P_{\mathrm{purch}}/P_{\mathrm{sold}}$	Power purchased/sold from/to the main grid [kW]
$P_{ess}^{ch}/P_{ess}^{\mathrm{dis}}$	Charging/Discharging power of BESS [kW]
P_{demand}	Load demand in the microgrid [kW]
β_{bp}/β_{sp}	Purchasing/selling status of power from the main grid; binary variable
$\alpha_{ess}^{ch}/\alpha_{ess}^{\mathrm{dis}}$	Charging/Discharging status of BESS; binary variable
α_{cg}	Off(0)/on(1) status of a controllable generator; binary variable
α_{cg}^{su}	Off(0)/on(1) status of a controllable generator at start-up; binary variable
Abbreviations	
EM	Energy management
MG	Microgrid
RES	Renewable energy source
WT	Wind turbine
PV	Photovoltaic
CG	Controllable generator
WP	Water pump
ET	Electric tractor
BESS	Battery energy storage system
Li-ion	Lithium-ion
RUL	Remaining useful life
SOC	State of charge
SOH	State-of-health
EOL	End of Life
DOD	Depth of discharge
C-rate	Current rate
COA	Coati optimization approach
ML	Machine learning
SVR	Support Vector Regressio

CNN	Convolutional Neural Network
LSTM	Long Short-Term Memory
TCN	Temporal Convolutional Network
XGBoost	eXtreme Gradient Boosting
LightGBM	Light Gradient-Boosting Machin
RMSE	Root Mean Squared Error
MAPE	Mean Absolute Percentage Error
PSO	Particle swarm optimization
MCS	Monte Carlo Simulation

capabilities, to compensate for unreliable grid connections [4]. To enhance reliability and stability, BESSs are integrated to store the excess energy of RES and supply MGs during periods of high demand or grid outages. However, the variable nature of agricultural energy consumption and the added complexity of BESS degradation pose significant challenges. Accurate modeling of battery degradation is essential to optimizing both energy storage and overall system performance, ensuring long-term resilience and cost-effectiveness in agricultural MG operations. This research focuses on addressing these challenges by optimizing the integration of ESSs and RESs for agricultural MGs.

1.1. Literature review

Despite significant advancements in BESS technology, accurately predicting the RUL of Li-ion batteries remains challenging. Li-ion batteries undergo degradation over time due to various factors including their SOC, DOD, ambient temperature fluctuations, C-rate, and charging policies [5]. Limiting discharge cycles can mitigate the associated battery degradation and promote more sustainable and cost-effective energy storage utilization [6], reduce the safety issues, and increase thermal stability [7]. Predicting the RUL of Li-ion batteries falls into two categories: physics-based and data-driven modeling. Physics-based methods include empirical and semi-empirical battery degradation models that typically include linear degradation models or models based on DOD and SOC of the battery [8]. Authors in [9] employ information about the battery's DOD to compute the RUL in terms of cycles and predict the battery degradation mechanism. With a focus on DOD and SOC, Refs. [10,11] provide a model to capture the degradation pattern for Li-ion batteries throughout the battery's lifespan, which may not accurately reflect real-world conditions due to unstable environmental conditions, specifically temperature and not considering the other influential factors such as the battery charging/discharging C-rate. With the same argument, the linear modeling approaches for battery degradation analysis presented in [12,13] do not provide adequate accuracy for predicting the RUL of Li-ion batteries for many applications.

Recent developments in employing data-driven models based on SOC [14], SOH [15], and EOL of batteries [16], have demonstrated considerable potential in predicting the RUL of Li-ion batteries [17]. Notably, models such as Random Forest [18], LSTM [19], LightGBM [20], SVR [21], CNN-LSTM [22], and TCN [23] stand out for this purpose. Due to the diverse range of ML-based approaches, the authors performed a comparative analysis to assess the predictive capabilities of various ML models for Li-ion battery RUL prediction in their previous study [24]. This study highlights the performance trade-offs and suitability of different ML models for this specific task. Among these models, the XGBoost model emerges as the top performer, achieving superior results in terms of RMSE and MAPE of the RUL prediction. Enhancing the prediction accuracy of RUL of Li-ion batteries, particularly concerning their remaining cycle life, holds promise for optimizing BESS utilization within power systems.

Optimal scheduling of BESSs is among the key tasks in the EM system of MGs. In [25], BESSs are integrated within a distribution network for peak load shaving, power demand smoothing, and voltage regulation. Authors in [26] explore the optimal modeling of the BESS within a distribution network. The study results reveal enhanced voltage profiles, minimized reactive power flow, decreased network losses, and a cost-effective charging/discharging strategy of BESSs. In [27], authors investigate the impact of integrating BESSs into the MG for assessing the operational cost of the system using a multi-objective optimization method. Although the potential impacts of integrating BESSs into power systems have been explored in many studies, the degradation of BESSs and the associated costs are commonly overlooked [28,29]. Consequently, integrating the degradation model of BESSs can provide a more comprehensive understanding of the overall operational costs of the network and their applicability within power systems.

In [30], a linear model is presented that incorporates calendar aging and cycle aging of the battery, accounting for its degradation costs. Subsequently, this degradation cost is incorporated into a predictive EM problem. Despite the linearity of the proposed algorithm and the factors considered, the results demonstrate the efficacy of considering the degradation of BESS when optimizing the charging/discharging strategy of the battery. In [31], the authors explore optimal EM for community-based MGs. The study considers the degradation cost of batteries by including a penalty factor to constrain charging/discharging cycles, and the PSO algorithm is used to solve the optimization problem. In [32], a BESS scheduling approach is introduced while considering the degradation cost of the battery. The proposed method employs a two-stage formulation and considers a one-cycle life characteristic and battery discharge SOC-based degradation. Notably, this formulation can be utilized specifically for deterministic optimization problems. In [33], authors investigate the battery scheduling problem using a semi-empirical-based linear model to account for battery degradation costs. This linearized model, leveraging the RUL of the battery, is integrated into a model predictive control algorithm for effective EM of the battery. Other commercial models of BESS degradation costs [34] often fall short in accurately predicting the SOC and DOD of the battery. This can lead to an inadequate representation of degradation costs in the battery scheduling problem, highlighting the need for improved battery degradation models.

1.2. Novelty and contribution

In this paper, we introduce a novel approach to address the power management problem of an agricultural MG taking into account the capacity degradation of the BESS. Our study is based on a real-world agricultural MG in Ankara, Turkey, providing practical insights into MG operations. Leveraging insights from existing literature, we develop an XGBoost model to predict the RUL of the battery, enabling accurate estimation of battery degradation rates across cycles. Furthermore, to evaluate the robustness of the proposed methodology, we employ MCS to generate multiple scenarios. These scenarios encompass varying levels of RES penetration, as well as fluctuations in the electricity price and MG's load demand. In addition, we employ COA to determine the optimal charging and discharging policies related to the cycle limitations of the BESS. The main contributions made by this paper are as follows:

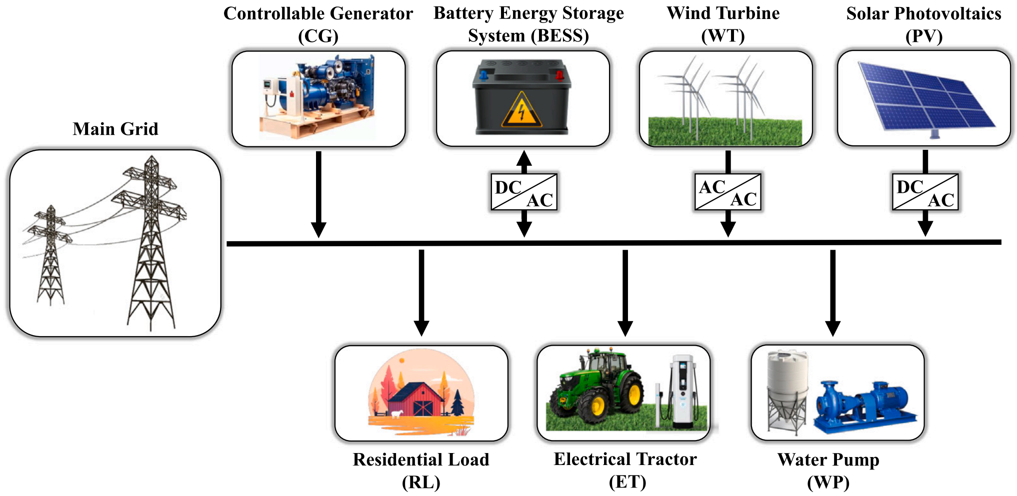

Fig. 1. Structure of the agricultural MG under consideration.

- Proposing a day-ahead energy management system for an agricultural MG considering battery degradation.
- Developing an XGBoost ML model to predict the RUL of the BESS of the MG.
- Developing an optimization problem to optimize the charging and discharging rates of the BESS using the COA.
- Using the MCS approach to generate multiple scenarios for the RES penetration level, electricity price, and power demand of the MG to perform a sensitivity analysis of the energy management strategy.

1.3. Paper organization

The rest of the paper is organized as follows: Section 2 introduces the energy management problem of the agricultural MG integrated with BESSs. Section 3 elaborates on the proposed methodology to model battery degradation using the XGBoost model and COA for the optimal scheduling of the agricultural MG. Subsequently, Section 4 presents the case studies and simulation results. Finally, Section 5 concludes the paper.

2. Problem statement

This section introduces the operation management problem of an agricultural MG, which is illustrated in Fig. 1. The system comprises two CGs with a rated power of 10 kVA each, and RESs including WTs and PVs with output powers of 10 kW and 12 kW, respectively. Additionally, it incorporates a BESS with a power capacity of 5 kW and an energy capacity of 10 kWh. It also includes vital components for agricultural operations, such as ETs, WPs, and residential loads. ETs operate daily from 4:00 PM to midnight and recharge from midnight to 4:00 PM. They require 20 kWh of energy to be fully charged and ready for operation. WPs are set to function between 00:00 to 16:00, for 5 h in total consuming 3 kWh energy per hour to fill the water reservoir. This reservoir serves the essential purpose of daily irrigation for the agricultural lands, ensuring consistent water supply to support crop growth and maintenance. These schedules are set according to the agricultural farm's needs, ensuring maximum utilization of renewable energy from PVs and WTs. The timing of daily farm operations should be aligned with periods of high solar and wind energy availability to maximize the use of renewable power and minimize reliance on stored energy in BESSs. This strategic operation and battery utilization reduce the operational costs of the agricultural MG, while also enhancing the overall efficiency and sustainability of agricultural practices. In Section 2.1, the conventional energy scheduling problem of the agricultural MG without considering the battery degradation mechanism and its associated cost is introduced. Subsequently, in Section 2.2, the importance of battery degradation cost modeling is presented.

2.1. Energy management problem of the agricultural MG

The energy management problem of the agricultural MG refers to the optimal scheduling of the flexible power demand, battery charging/discharging, and the power exchange with the main grid, while satisfying the technical and operational requirements. The subsequent Eqs. (6) to (18), detail the technical constraints governing the components within the agriculture MG. These equations define the operational boundaries and requirements for each component. The objective function, aimed at minimizing operational costs, is formulated in Eq. (1). Eq. (2) represents the power balance of the MG. The generated power includes the power from CGs, WT, and PV units, discharge power of BESSs, and purchased power from the main grid. The consumed power encompasses the total electrical load demand of the agricultural MG (P_{demand}) including the residential load and the power demand from the ET and the WP, the charging power of BESS, and the power sold to the main grid.

The output power of CGs is regulated by constraints described in Eqs. (3) to (5). Eq. (3) ensures the output power of CGs stays within specified maximum and minimum limits. Eq. (4) controls the rate at which CGs can increase their output power (ramp up), while Eq. (5) governs the rate at which they can decrease their output power (ramp down). Eq. (6) facilitates either purchasing or selling power to or from the main grid, preventing simultaneous power exchange. Furthermore, Eq. (7) introduces the thermal limitations of tie-lines between the main grid and the MGs, ensuring the satisfaction of thermal constraints. Eqs. (8) and (9) are presented to limit the status of BESS, even in charging or discharging mode, and its operational limitation to keep charging and discharging power within their maximum and minimum levels. Eqs. (10) and (11) are used to calculate the SOC and stored energy of the BESS unit. Eq. (12) mandates the final SOC of the BESS to be equal to the initial SOC value.

$$J = \sum_{t}^{t=24} \sum_{i}^{N} \left(OP_{cg}(t,i) C_{cg}(i) + \alpha_{cg}(i) C_{cg}^{nl}(i) + \alpha_{cg}^{su}(i) C_{cg}^{su}(i) \right) + \left(P_{purch}(t) EP(t) - P_{sold}(t) ES(t) \right) \tag{1}$$

$$\sum_{i}^{N} \left(OP_{cg}(t,i) + P_{WT}(t) + P_{PV}(t) + P_{\text{ess}}^{\text{dis}}(t) \right) + P_{\text{purch}}(t) - P_{\text{sold}}(t) = P_{\text{demand}}(t) + P_{\text{agri}}(t) + P_{\text{ess}}^{ch}(t) \quad ,\forall t \tag{2}$$

$$OP_{cg}^{\min}(i) \leq OP_{cg}(t,i) \leq OP_{cg}^{\max}(i) \quad ,\forall i,t \tag{3}$$

$$OP_{cg}(t,i) - OP_{cg}(t-1,i) \leq \Delta T.RL_{cg}^{\text{up}}(i), \quad \forall i,t \tag{4}$$

$$OP_{cg}(t-1,i) - OP_{cg}(t,i) \leq \Delta T.RL_{cg}^{\text{down}}(i), \quad \forall i,t \tag{5}$$

$$\beta_{\text{bp}}\ (t) + \beta_{\text{sp}}\ (t) \leq 1, \quad \forall t \tag{6}$$

$$\begin{cases} 0 \leq P_{\text{purch}}(t) \leq \beta_{\text{bp}}(t)\text{Th}_{\text{grid}}^{\max} \\ 0 \leq P_{\text{sold}}(t) \leq \beta_{\text{sp}}(t)\text{Th}_{\text{grid}}^{\max} \end{cases}, \quad \forall t \tag{7}$$

$$\alpha_{\text{ess}}^{\text{dis}}\ (t) + \alpha_{ess}^{ch}(t) \leq 1, \quad \forall t \tag{8}$$

$$\begin{cases} \alpha_{ess}^{ch}(t)P_{ess,ch}^{\min} \leq P_{ess}^{ch}(t) \leq \alpha_{ess}^{ch}(t)P_{ess,ch}^{\max} \\ \alpha_{ess}^{dis}(t)P_{ess,dis}^{\min} \leq P_{ess}^{dis}(t) \leq \alpha_{ess}^{dis}(t)P_{ess,dis}^{\max} \end{cases}, \quad \forall t \tag{9}$$

$$SOC_{\text{ess}}\ (t) = \frac{EC_{ess}(t)}{EC_{\text{ess}}^{\max}}, \quad \forall t \tag{10}$$

$$EC_{ess}(t) - EC_{ess}(t-1) + \Delta T\left(\frac{P_{ess}^{dis}(t-1)}{\xi_{ess}^{\text{dis}}} - \xi_{ess}^{ch}P_{ess}^{ch}(t)\right) = 0, \forall t \tag{11}$$

$$EC_{\text{ess}}^{t_{24}} = EC_{\text{ess}}^{t_0} \tag{12}$$

2.2. Integrating battery degradation model into energy management problem

The necessity of integrating the battery degradation model into the energy management strategy cannot be overstated. Battery degradation significantly affects both the economic and technical performance of BESSs. Over time, repeated charging and discharging cycles lead to a decrease in battery capacity and efficiency. By incorporating a degradation model, operators can optimize the use of batteries, extend their operational lifetime, and reduce their total life cycle costs. This approach ensures optimal operation of BESSs, which delays BESSs degradation and maximizes return on investment [3].

Moreover, optimal battery utilization informed by degradation modeling is crucial for maintaining the reliability of MGs. A detailed understanding of how battery performance deteriorates over time enables more accurate forecasting of battery life and better scheduling of charging and discharging cycles. This strategic management approach maintains a balance between immediate energy demands and long-term battery health while enhancing the stability and sustainability of MG operations. The integration of this model not only supports the economic aspects by optimizing operational costs but also contributes significantly to the environmental goals of reducing waste [3]. In the following section, the proposed method for incorporating the battery degradation model into the energy management problem is presented.

3. Proposed methodology

In this section, the proposed methodology for the optimal day ahead operation scheduling of the agricultural MG is introduced, while the battery degradation mechanism and its associated costs are taken into account. In this line, first, a data-driven strategy is introduced to model battery degradation using predictive analytics techniques to accurately capture the C-rate, SOC, and DOD patterns of the battery over its operational lifespan. Subsequently, the operation management problem of the agricultural MG introduced in the previous section is reformulated to incorporate the degradation cost of the battery. Several scenarios are generated using the Monte Carlo approach to account for the fluctuation of the output power of RESs and variations in electricity prices and residential loads. By developing scenarios, the inherent uncertainties and variability in renewable energy availability, power consumption, and market conditions are captured, enhancing our optimization framework's robustness Finally, the COA is used to solve the energy management problem. COA offers a powerful optimization tool that handles complex, multi-dimensional objectives and constraints inherent in the MG scheduling problem.

3.1. Battery degradation modeling

In this subsection, the concept of the proposed methodology for battery degradation modeling is introduced. As highlighted in the literature review, data-driven models offer a robust approach for capturing the patterns associated with C-rate, SOC, and DOD characteristics exhibited by batteries over their operational lifespan. These patterns are important indicators of the underlying degradation mechanisms affecting battery performance. Utilizing a dataset specific to Li-ion batteries, which will be elaborated upon in Section 3.1.1, an XGBoost model is developed by employing SOC, DOD, C-rate, and temperature of the Li-ion battery of the agricultural MG to predict its RUL. By predicting the RUL accurately, our model estimates the battery degradation incurred during each operational cycle. From the results of the RUL prediction, the degradation in each cycle is calculated, which is then translated into the degradation cost of the battery associated with that specific cycle. This approach allows us to incorporate the dynamic nature of battery degradation into our optimization framework, facilitating a more comprehensive analysis of the long-term performance and costs of the MG. The proposed model to determine the battery degradation cost is presented in the following.

3.1.1. Data preprocessing

The dataset used for training and validating the XGBoost model was obtained from [35] and through comprehensive battery simulation analyses conducted using MATLAB Simulink software. This dataset includes 945 distinct battery aging tests, covering various influential parameters such as SOC, DOD, temperature, and C-rate. Within the simulation model, ambient temperature, battery aging mechanism, and dynamic change of the battery's internal resistance are simulated. Fig. 2 presents the distribution of battery cycle life and battery aging test counts considering various SOC and DOD values. The dataset is divided into two distinct categories: training and testing. In this partitioning, 80% of the data is allocated for training purposes, while the remaining 20% is reserved for testing the model's performance. This division ensures that the model is trained on a sufficient dataset while maintaining a separate set for evaluating its generalization capabilities. By feeding the extracted features to the XGBoost model, the XGBoost model can learn the complex relationships between battery aging parameters and capacity degradation. This enables the XGBoost model to accurately predict battery RUL, which can be used to estimate the degradation cost of the battery in each cycle.

3.1.2. XGboost model for predicting battery degradation

The XGBoost model is a powerful machine learning algorithm widely utilized for various predictive modeling tasks, including regression and classification [36]. It belongs to the ensemble learning family, specifically the gradient boosting framework, known for its ability to produce highly accurate predictions by combining the strengths of multiple weak learners. Its strong performance in real-world scenarios has been validated through extensive research, including the case studies presented in [24], which demonstrate its accuracy and reliability in practical engineering applications. In this paper, the XGBoost model is selected due to its proven effectiveness in predicting battery degradation. However, due to space limitations and the primary focus of this work being the integration of an efficient battery degradation prediction model with the EM system of MGs, the detailed formulation and implementation of the XGBoost model are not included here.

The mathematical formulation of the XGBoost model involves constructing an ensemble of decision trees iteratively, with each subsequent tree attempting to correct the errors of the previous ones [24]. The final prediction is obtained by aggregating the predictions of all individual trees. Let denote the dataset as $D = \{(x_i, y_i)\}_{i=1}^{N}$, where x_i represents the features of the ith instance and y_i represents the corresponding label. The XGBoost model aims to learn a predictive function $F(x)$ that minimizes a predefined loss function $L(y_i, F(x_i))$ over

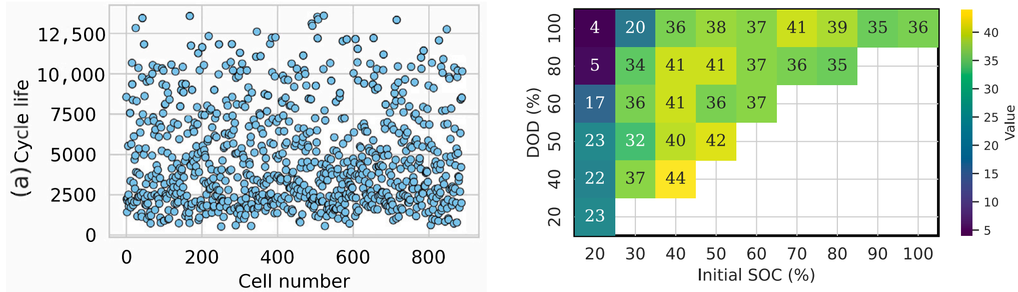

Fig. 2. Distribution of battery cycle life (a), and battery aging test counts across different SOC and DOD conditions (b).

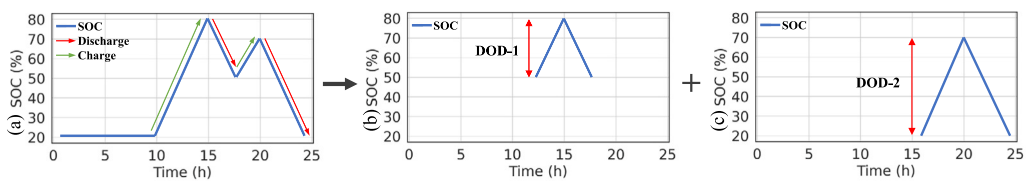

Fig. 3. Battery SOC for a sample data for 24 h (a), splitting the first peak to the next valley as a DOD-1 (b), and second peak to the second valley as a DOD-2 (c).

the training data. The objective function of the XGBoost model can be represented as Eq. (13).

$$\mathrm{Obj}(\Theta) = \sum_{i=1}^{N} L(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{13}$$

Here, Θ denotes the set of model parameters, $L(y_i, \hat{y}_i)$ represents the loss function, f_k represents the kth tree in the ensemble, and $\Omega(f_k)$ represents a regularization term penalizing the complexity of the trees. At each iteration, the XGBoost model adds a new decision tree f_k to the ensemble by fitting it to the negative gradient of the loss function with respect to the predictions of the previous ensemble as Eq. (14) presents.

$$f_k = \arg\min_f \sum_{i=1}^{N} L(y_i, \hat{y}_i^{(t-1)} + f(x_i)) + \Omega(f) \tag{14}$$

The final prediction (Eq. (15)) of the XGBoost model for a new instance x is obtained by summing the predictions of all individual trees:

$$F(x) = \sum_{k=1}^{K} f_k(x) \tag{15}$$

Two key performance metrics namely MAPE and RMSE are used to evaluate the performance of the developed XGBoost model to predict the battery RUL [37]. Mathematical expressions representing RMSE and MAPE are provided in (16) and (17):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{16}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{17}$$

where y_i and $\hat{y}_i$ indicate the actual and predicted values, respectively.

3.2. Battery degradation cost estimation

This subsection presents a core contribution of this paper, specifically the derivation of battery degradation costs using the developed XGBoost model. These costs will be incorporated into the resultant operational costs of the agricultural MG, thereby providing a comprehensive assessment of the overall cost while considering battery degradation. The methodology begins with the specification of the input vector for the XGBoost model, as detailed in Eq. (18). For the DOD calculation, each valley within the SOC curve is first identified and isolated, and then a DOD value for each identified valley is calculated. This procedure is visually detailed in Fig. 3. Subsequently, the RUL is calculated using the XGBoost model, as represented in Eq. (19). The workflow used to predict the RUL of the BESS with the XGBoost model is presented in Fig. 4. The degradation rate for each hour is calculated using the predicted RUL value, as defined in Eq. (20). Since the degradation rate is determined hourly, each cycle in this formula corresponds to one hour. The $\mathrm{SOH_{initial}}$ is defined as 1, representing 100% health, while $\mathrm{SOH_{final}}$ is set to 0.8, indicating 80% health. Both SOH values are dimensionless and signify the percentage of the battery's capacity. Additionally, the unit for RUL is cycles. Finally, the total degradation cost for 24 h is calculated, taking into account the price of a brand-new ($\kappa_{bn,batt}$) and a salvaged battery ($\kappa_{slvg,batt}$) as can be seen in Eq. (21).

$$x_{\mathrm{t}} = \begin{bmatrix} \mathrm{SOC}_t \\ \mathrm{DOD}_t \\ \text{C-rate}_t \\ \mathrm{Temperature}_t \end{bmatrix}, \quad \forall t \tag{18}$$

$$RUL_t = f^{\mathrm{XGBoost}}\left(x_t\right), \quad \forall t \tag{19}$$

$$\text{Deg-rate}_t = \frac{\left(\mathrm{SOH_{initial}} - \mathrm{SOH_{final}}\right)}{RUL_t}, \quad \forall t \tag{20}$$

$$\text{Deg-cost} = \sum_{t=1}^{24} \text{Deg-rate}_t \left(\kappa_{bn,batt} - \kappa_{slvg,batt}\right) \tag{21}$$

3.3. Scenario generation for uncertainty management

The MCS method is employed to capture uncertainties inherent in renewable energy generation, specifically PVs and WTs, as well as the volatility of electricity prices and load demand. Five stages are employed to implement the MCS approach for scenario generation of the components of the agricultural MG as follows [38]:

- Assigning a probability density function (PDF) to each uncertain variable.
- Generating N possible values for each input data by sampling from its respective PDF based on mean and standard deviation.

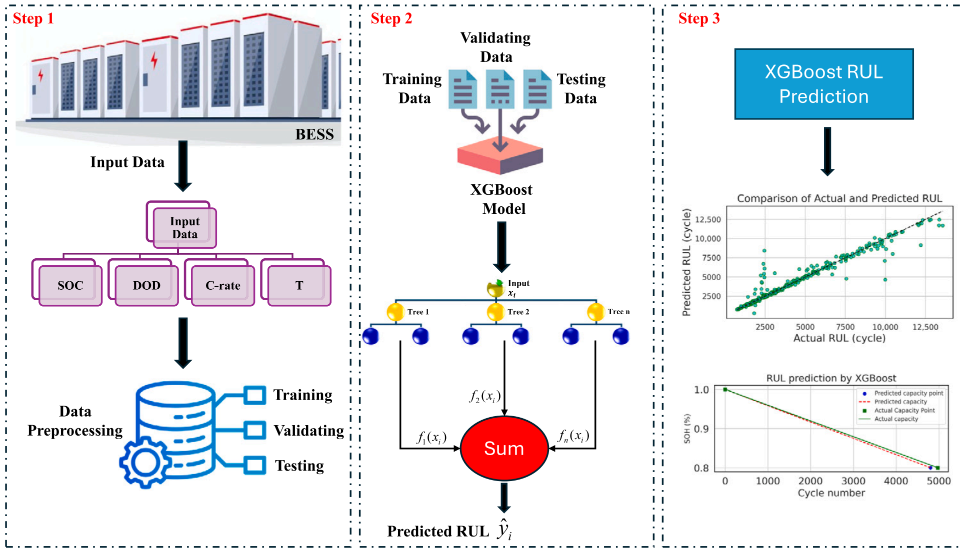

Fig. 4. Workflow of the proposed strategy to predict RUL of the battery using XGBoost model.

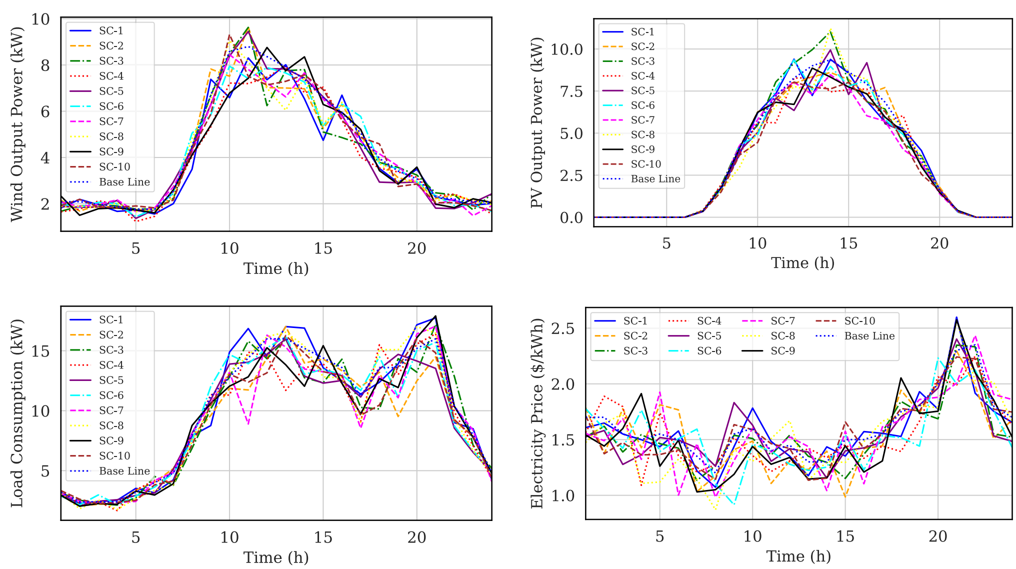

Fig. 5. Generated scenarios for wind output power (a), PV output power (b), load consumption (c), and electricity price (d).

- Combining the random samples to form N input vectors.
- Executing the simulation of the model N times, once for each input vector. This process yields a vector of results and establishes an input–output mapping of the model.
- The probability density function of the simulation outcome is defined by the collection of output data.

3.4. Coati optimization approach

The COA is a nature-inspired meta-heuristic algorithm that mimics the foraging strategies of coatis, intelligent mammals known for their collaborative food searching [39]. As coatis use their snouts to unearth food hidden underground, COA explores the solution space of an optimization problem to uncover optimal or near-optimal solutions. This population-based algorithm employs a collection of candidate solutions, each representing a potential answer to the problem. These candidates are continuously refined through a series of procedures: exploration, exploitation, and selection. Exploration introduces new solutions into the population, often utilizing random search techniques like uniform or Gaussian sampling. This step allows the algorithm to broadly investigate the solution space. Exploitation focuses on improving existing solutions through local search methods such as hill climbing or simulated annealing, ensuring the algorithm thoroughly explores promising regions. Selection carefully chooses the fittest solutions from the population to guide the search towards the most promising areas. This iterative process of exploration, exploitation, and selection continues until a predefined stopping criterion is met, which could be a maximum number of iterations, a time limit, or the achievement of a desired level of convergence. Mathematically, the COA's solution update mechanism can be expressed as:

$$Y_{t+1} = Y_t + \gamma(Y_t - Y_{opt}) + \delta(Y_t - Y_{rand}) \tag{22}$$

where Y_t represents the current population of solutions, Y_{t+1} is the updated population, Y_{opt} denotes the best solution discovered so far, Y_{rand} is a randomly selected solution, and the parameters γ and δ control the balance between exploration and exploitation. The COA's strengths lie in its robustness, low computational complexity, efficient information sharing among solutions, and rapid convergence [40]. These characteristics make it well-suited for optimizing the hyperparameters of the proposed model, as detailed in the following section.

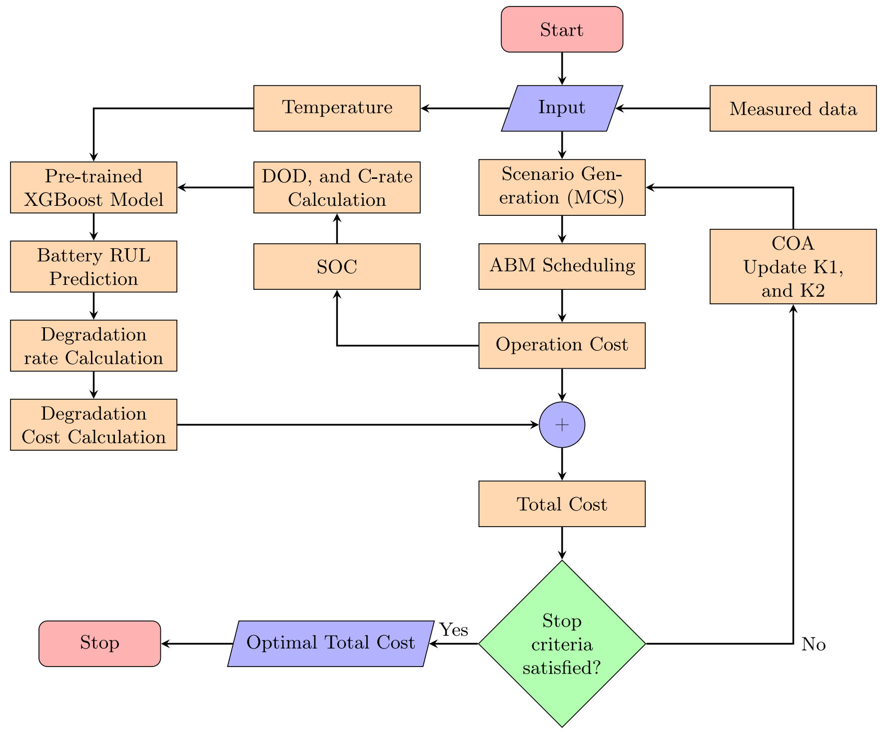

Fig. 6. Flowchart of the proposed methodology for MG operation scheduling.

3.5. Applying COA to the ESS scheduling

ESSs help reduce MG operational costs by storing excess energy during low demand or when RESs produce more electricity. A lower charging/discharging rate may increase reliance on grid power during peak demand, raising operational costs. Conversely, reducing these rates decreases the usage of ESSs, and consequently the degradation cost of the ESSs. However, increasing the charging and discharging rates, while reducing the total operational cost of the MG, raises the degradation cost of the ESSs. Therefore, finding the optimal values of charging and discharging rates is crucial to minimizing both the total cost of MG operation and ESS degradation. In this paper, COA is employed to optimize these rates by determining the optimal values of K1, and K2 expressed in Eqs. (23) to (26). These values are selected by the COA to effectively regulate the charging and discharging rates of the ESS, achieving a balance between operational efficiency and longevity of the ESS.

$$\sum_{t,i} P_{\mathrm{ess}}^{\mathrm{ch}}(t,i) \leq K_1 P_{\mathrm{ess}}^{\mathrm{ch\_max}} \tag{23}$$

$$\sum_{t,i} P_{\mathrm{ess}}^{\mathrm{dis}}(t,i) \leq K_2 P_{\mathrm{ess}}^{\mathrm{dis\_max}} \tag{24}$$

$$0.2 \leq K_1 \leq 1 \tag{25}$$

$$0.2 \leq K_2 \leq 1 \tag{26}$$

The detailed procedure of the proposed methodology is depicted in the flowchart illustrated in Fig. 6. Initially, the input data enters the MCS block, generating diverse scenarios essential for the subsequent agricultural MG scheduling. Then, operational costs are computed alongside the SOC values of the BESS. Subsequently, the C-rate and DOD are calculated from the SOC. The resulting SOC, DOD, C-rate values, and temperature data are then fed into the XGBoost module, facilitating the calculation of battery RUL and degradation rate that is used to obtain the battery degradation cost. Afterward, the total costs, comprising the operational cost of the MG and the battery degradation cost, are aggregated. If the stop criteria are not satisfied, the COA will adjust K_1 and K_2 and the power scheduling of the MG coefficients to achieve an optimal total cost, ensuring a feasible operating schedule and optimal performance.

4. Case study and numerical results

In this section, different case studies are investigated to assess the performance of the proposed methodology. The agricultural MG structure is according to Fig. 1. As described in Section 3.3, scenarios are generated using MCS to account for the uncertainties in RES and the fluctuations in electricity prices and load demand. The data utilized for the agricultural MG is sourced from real-world datasets [41] specific to Ankara, Turkey, ensuring the relevance and applicability of the model to practical scenarios. The proposed methodology is modeled in the Python environment (V3.9) on a personal computer. The first case study examines the presence of power exchange between the agricultural MG and the upstream grid, by considering two scenarios: one incorporating battery degradation cost and the other without. In the second case, no power exchange is considered between the agricultural MG and the main grid, representing the islanded mode of operation, while considering battery degradation cost to evaluate the charging and discharging patterns of the BESS and its associated costs. Finally, the third case investigates the volatility of RES available power, electricity price, and load demand using scenarios generated by MCS to conduct a comprehensive sensitivity analysis. These case studies are summarized as follows:

- Case 1: Grid-connected mode with and without considering battery degradation.
- Case 2: Island mode with and without considering battery degradation.
- Case 3: Sensitivity Analysis

4.1. Numerical results of case 1

In this case, the agricultural MG can exchange power with the main grid. Consequently, the MG engages in both selling and buying power

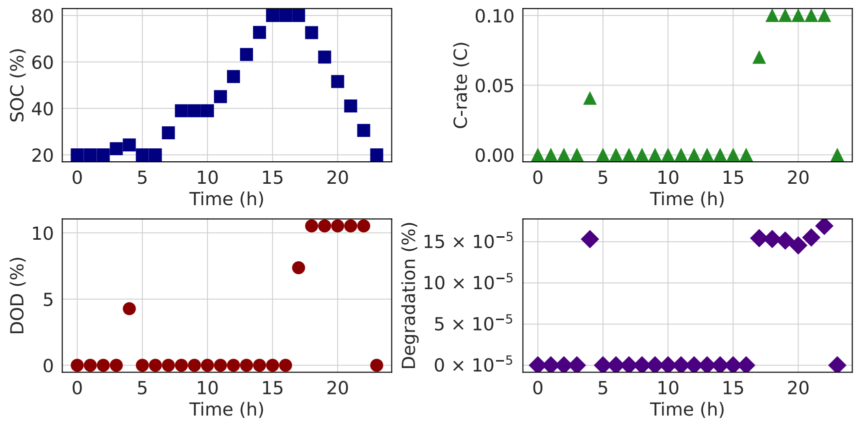

Fig. 7. SOC (a), C-rate (b), DOD (c), and degradation rate obtained from XGBoost model (d).

transactions. It procures additional power from the grid to meet its load requirements (buying) and sells excess generated power back to the grid when its generation exceeds local demand. Fig. 7-(a) illustrates the SOC resulting from solving the agricultural MG scheduling problem. Subsequently, the C-rate 7-(b) and DOD 7-(c) are derived from the SOC, enabling the XGBoost model to calculate the hourly degradation rate 7-(d) for each discharge value of ESS. Table 1 and Fig. 8 represent the power generation and consumption patterns, as well as the resulting total cost, including degradation cost, alongside the operation cost for the agricultural MG. From the table, it is observed that three distinct sets of values derived by the COA for parameters K1 and K2: the upper bound (K1 = K2 = 1, case1.1), the lower bound (K1 = K2 = 0.2, case1.3), and the optimal values (K1 = 0.205, K2 = 0.5 as case1.2). The upper bound values suggest that the agriculture MG operator adopts the conventional MG operation management strategy without taking into account battery degradation. This is evidenced by the discharge of stored energy by the BESS to meet demand at hour 21:00, as illustrated in the figure. Conversely, with lower bound K values, the agricultural MG operator adopts a conservative approach, resulting in the discharge of stored energy over 6 h, from hour 18:00 to hour 23:00, which corresponds to higher degradation rates during each cycle.

According to Table 1, in Case 1.1, the operation cost is the lowest among the three cases, amounting to 69.54 Lira. However, the degradation cost is the highest, totaling 52.61 Lira. The combination of these costs results in a total daily cost of 122.15 Lira. Although this case minimizes operation costs, but it suffers from a high degradation cost. Case 1.2 demonstrates a balanced approach by utilizing a mix of grid electricity and battery power. While the total operation cost (69.73 Lira) is slightly higher than Case 1.1, the significant reduction in the total degradation cost (29.01 Lira) results in the lowest overall cost (98.74 Lira) among all three grid-connected scenarios. This highlights the importance of strategically balancing operational costs with battery degradation for long-term cost optimization. In this scenario, the increase in operation costs is smaller than the reduction in battery degradation costs, making this the most cost-effective configuration in the grid-connected MG scenario.

Case 1.3 prioritizes the battery utilization over the grid electricity. This leads to the highest total operation cost (71.32 Lira) among the grid-connected cases due to the reliance on more grid electricity power. While it yields the lowest degradation cost (29.01 Lira), the high operation cost results in a higher overall cost (136.23 Lira) than Case 1.2. This emphasizes that excessive reliance on batteries, even with lower degradation, can be economically unfavorable. While operation costs are reduced in this case, the significant increase in degradation costs far outweighs the savings. This highlights the importance of balancing both operation and degradation costs to avoid scenarios where reduced operational expenses lead to higher long-term maintenance costs.

Table 1
Comparison of daily cost values for the grid-connected agricultural MG under different scenarios.

Case number	K1	K2	Total operation cost (Lira)	Total degradation cost (Lira)	Total cost (Lira)
Case 1.1	1	1	69.54	52.61	122.15
Case 1.2	0.205	0.5	69.73	29.01	**98.74**
Case 1.3	0.2	0.2	71.32	64.91	136.23

Table 2
Comparison of daily cost values for the islanded agricultural MG under different scenarios, by considering BESSs degradation costs.

Case number	K1	K2	Total operation cost (Lira)	Total degradation cost (Lira)	Total cost (Lira)
Case 2.1	1	1	87.44	36.81	124.25
Case 2.2	0.27	0.73	90.19	17.46	**107.65**
Case 2.3	0.2	0.2	90.81	29.71	120.52

The corresponding degradation costs for Case 1.1 and Case 1.3 are 52.6 and 64.9 Lira, respectively. Moreover, the total costs associated with these approaches are 122.05 Lira and 136.25 Lira, respectively. In contrast, for the optimal values found by COA marked as Case 1.2 (K1 = 0.205 and K2 = 0.5), the stored energy of the BESS is discharged over 3 h, contributing to a 55.30% reduction in degradation costs and a 27.51% reduction in the total cost compared to Case 1.3. Furthermore, in Case 1.2, the BESS was charged in various steps with lower amounts of energy during the power generation of PV and WT according to their availability. Hence, incorporating the proposed battery degradation modeling into the agricultural MG scheduling has led to a reduction in the total cost.

4.2. Numerical results of case 2

In this case, the agricultural MG operates in the islanded mode, meaning there is no power exchange with the main grid. Residential loads, ETs, and WPs are primarily powered by RES and CGs. Similar to the previous case, the COA has been utilized to optimize the generation, consumption, and charging/discharging patterns of BESS units while considering the battery degradation costs. According to Table 2, Case 2.1 prioritizes a specific energy source- a CG in this islanded context-resulting in a moderate operation cost (87.44 Lira) and the highest degradation cost (36.81 Lira). This highlights that relying heavily on a single source, even in an islanded system, can lead to higher degradation costs. The operation cost is higher compared to the grid-connected case, reaching 87.44 Lira. The degradation cost is 36.81 Lira, leading to a total daily cost of 124.25 Lira. The islanded MG experiences higher operation costs compared to the grid-connected scenario, and

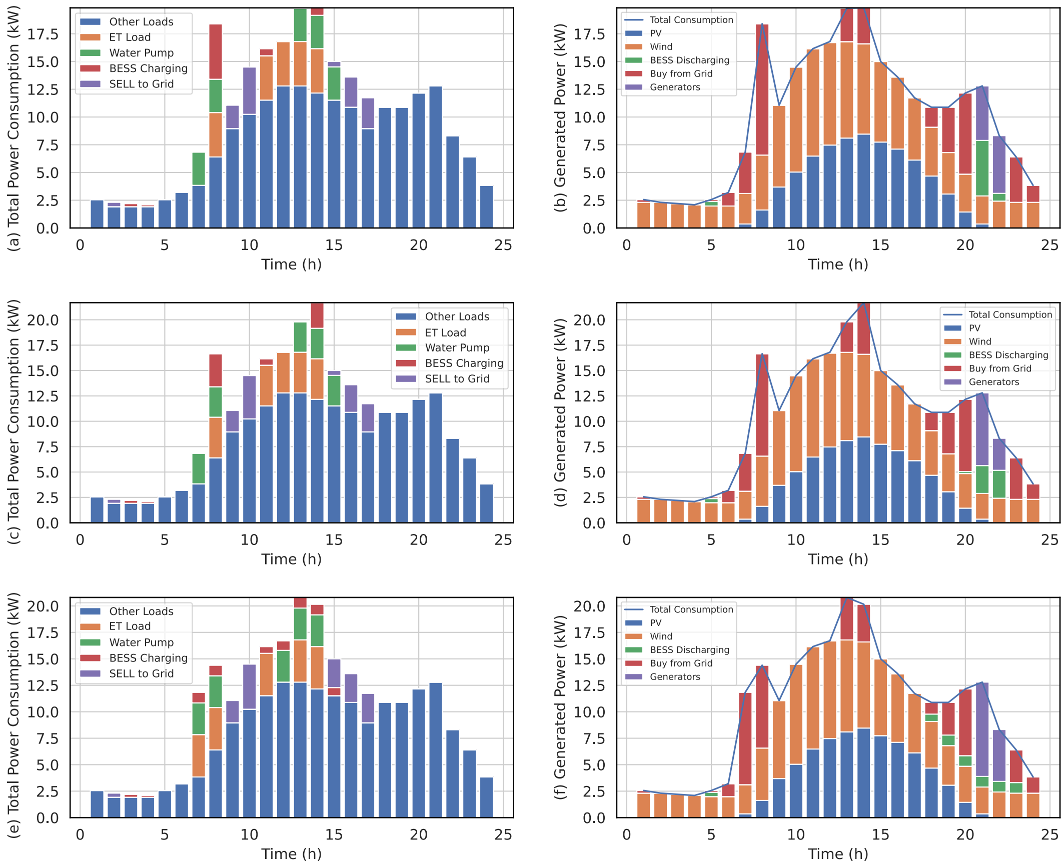

Fig. 8. Power generation and consumption for different cases (Case 1.1 (a and b), Case 1.2 (c and d), and Case 1.3 (e and f)).

the degradation cost is moderate. In addition, Case 2.2 represents a balanced energy strategy within the islanded system, utilizing a mix of battery power and other generation sources. It achieves the lowest total cost (107.65 Lira) by effectively balancing a slightly higher operation cost (90.19 Lira) with a significantly reduced degradation cost (17.46 Lira). Similar to Case 1.2, COA has found optimal values for K1 and K2, which achieves the most cost-effective balance by prioritizing the reduction of degradation costs. The slight increase in operation cost is outweighed by the substantial decrease in degradation costs, making this the optimal configuration for the islanded MG.

Ultimately, Case 2.3 prioritizes battery utilization, leading to the highest operational cost (90.81 Lira) due to the reliance on the potentially more expensive battery operation in the absence of a grid connection. However, it also achieves the lowest degradation cost (29.71 Lira) due to minimal cycling. While beneficial for battery health, the high operation cost results in a higher total cost (120.52 Lira) than Case 2.2. Although this case reduces the degradation cost compared to the baseline case (Case 2.1), it is not as effective as Case 2.2. The total daily cost is still higher than the optimal solution, illustrating that a more balanced approach, as seen in Case 2.2, is necessary to minimize both operation and degradation costs effectively.

As depicted in Fig. 9, the optimal values of k_1 and k_2 found by COA, Case 2.2, result in a significant reduction of 41.2% in degradation cost and 10.6% reduction in the total cost compared to case with lower bounds of k_1 and k_2. In this optimal scenario, the power generated by the CGs is minimized because the discharge pattern of the BESS effectively meets the agricultural MG's load demand in the islanded mode. Specifically, at hour 23:00, a significant portion of the demand is met by the discharge power of the BESS, rather than relying on the CG. In Case 2.1 and Case 2.3, the total costs of the agricultural MG are 124.25 Lira and 120.52 Lira, respectively. Similarly, when considering the lower bounds of K, Case 2.3, a more conservative approach from the agricultural MG operator is observed. This is evident in the increased utilization of the CG compared to the BESS. As anticipated, the overall costs including both operational and degradation costs increase during the islanded mode of operation. This is attributed to the increased utilization of CGs and BESS energy to fulfill the energy demands of the agricultural MG.

Table 3
Comparing cost values for islanded model in the different cases with degradation and Sell power.

Scenario number	K1	K2	Total operation cost (Lira)	Total degradation cost (Lira)	Total cost (Lira)
Baseline	0.205	0.5	69.73	29.01	**98.74**
SC-1	0.42	0.56	64.12	38.12	102.24
SC-2	0.29	0.41	66.14	44.99	111.13
SC-3	0.2	0.55	71.67	27.94	99.63
SC-4	0.24	0.35	58.22	46.65	104.87
SC-5	0.73	0.55	64.55	77.52	**142.07**
SC-6	0.48	0.45	61.53	45.77	107.30
SC-7	0.2	0.55	75.68	39.17	114.15
SC-8	0.3	0.66	70.76	31.60	102.36
SC-9	0.2	0.55	61.52	19.77	**81.32**
SC-10	0.35	0.48	71.49	49.58	117.07

4.3. Sensitivity analysis

In this subsection, scenarios generated by the MCS approach will be deployed to evaluate the robustness of the proposed methodology across different levels of RES penetration, as well as fluctuations in electricity prices and load demand. It is assumed that there is a power exchange between the agricultural MG and the grid. In Fig. 5, the scenarios generated through the MCS approach are observed which are then integrated into the optimization framework. For each scenario, the

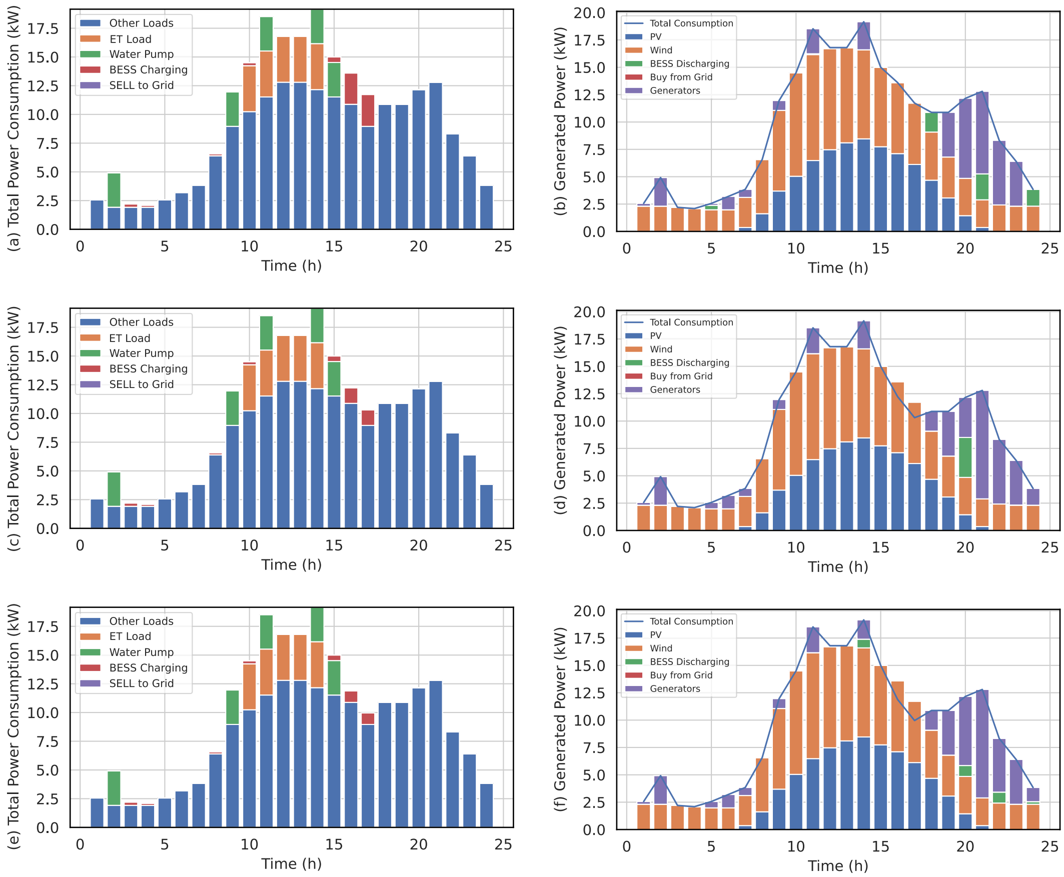

Fig. 9. Power generation and consumption for different cases (Case 2.1 (a and b), Case 2.2 (c and d), and Case 2.3 (e and f)).

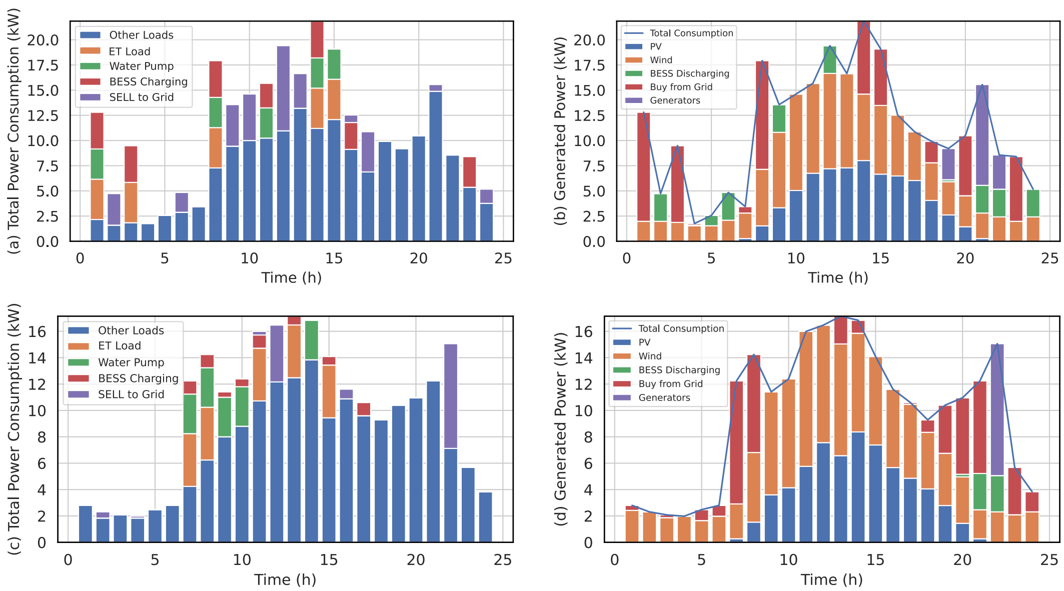

Fig. 10. Power generation and consumption for SC-9 (a and b), and SC-5 (c and d).

resulting operation cost, degradation cost, and total cost of the agricultural MG are recorded. Notably, the COA seeks to identify optimal values for k_1 and k_2 in each scenario. Table 3 presents the outcomes for each scenario, with SC-5 and SC-9 emerging as the worst and best cases, respectively. SC-9 is characterized by high renewable power availability, stable electricity prices, and load fluctuations, resulting in the lowest total cost of 81.32 Lira. Conversely, SC-5 exhibits lower RES outputs and increased fluctuations, resulting in a lower outcome. Fig. 10 further depicts the power generation and consumption patterns in SC-9 and SC-5, highlighting the discharge of stored energy of the BESS during peak daytime hours. This sensitivity analysis underscores the robustness of our proposed methodology, offering valuable insights for operators in navigating between different operating conditions and EM strategies.

4.4. Discussion and future work

The presented results demonstrate the effectiveness of integrating battery degradation modeling into the scheduling optimization of agricultural MGs. The COA successfully identified optimal operational strategies,for both grid-connected and islanded scenarios, leading to significant cost reductions. In the grid-connected mode, the optimization considered energy arbitrage with the main grid and battery degradation. Case 1.1, reflecting a conventional approach with no degradation awareness (K1 = K2 = 1), resulted in the lowest operational cost but the highest degradation cost due to battery utilization. Conversely, the conservative approach in Case 1.3 (K1 = K2 = 0.2) minimized degradation but at the expense of high operational costs due to increased reliance on the grid. The COA-determined optimal strategy (Case 1.2, K1 = 0.205, K2 = 0.5) effectively balanced these trade-offs. By strategically scheduling battery charging and discharging, it achieved a 55.30% reduction in degradation cost and a 27.51% reduction in total cost compared to the conservative approach, highlighting the economic benefits of incorporating degradation awareness. Operating in islanded mode, the MG relied on local generation, primarily from RES and CGs. Similar to the grid-connected scenario, the COA identified an optimal strategy (Case 2.2) that minimized overall cost by balancing the utilization of CGs and the battery. This optimal strategy resulted in a 41.2% reduction in degradation cost and a 10.6% reduction in total cost compared to the conservative Case 2.3, demonstrating the algorithm's effectiveness even under constrained generation resources. By strategically discharging the battery, particularly during peak demand periods, the reliance on CGs was minimized, reducing both fuel expenses.

Across both grid-connected and islanded modes, the results emphasize that while operational costs are important, degradation costs play a crucial role in determining the long-term economic performance of MGs. The optimized scheduling strategies identified through COA demonstrate that by carefully managing BESS discharge patterns, significant reductions in total cost can be achieved, even in scenarios with high operational demands or limited generation resources. This study underscores the critical importance of integrating battery degradation awareness into the optimization of agricultural MG operations. Ignoring degradation, as often seen in conventional approaches, leads to higher long-term costs due to battery utilization. Conversely, overly conservative strategies, while minimizing degradation, may result in excessive reliance on expensive generation sources like CGs or grid electricity. Our findings demonstrate the COA's effectiveness in encountering this trade-off. By strategically scheduling battery usage based on both operational and degradation costs, the COA achieved significant cost reductions in both grid-connected and islanded scenarios. This highlights the potential of incorporating intelligent optimization techniques and degradation-aware models for enhancing the economic viability and sustainability of future MGs.

Future research could explore the impact of different battery technologies, charging and discharging policies, and degradation models on optimization outcomes, potentially leading to more refined and cost-effective solutions. Investigating alternative battery types, alongside advanced degradation models, may enhance battery life predictions. Additionally, incorporating factors like electrode materials, which significantly affect degradation rates, could be applied to improve model accuracy and the optimization of EM systems, increasing the model's robustness in diverse MG applications.

5. Conclusion

This paper introduced an innovative approach to day-ahead operation scheduling of an agricultural MG, incorporating a data-driven battery degradation model. Utilizing real-world data from Ankara, Turkey, the MCS was employed to explore various scenarios, including renewable power from PV and WT units, price volatility, and load demand fluctuations, assessing the methodology's robustness in diverse operational conditions. An XGBoost model was developed to predict the RUL of Li-ion batteries and calculate the degradation rates in each discharge cycle. By integrating the predictive model into the scheduling framework, insights were obtained on optimizing battery usage patterns to minimize MG operating costs, while prolonging the operational lifespan and mitigating the degradation effects of the Li-ion batteries. Three case studies were conducted including the grid-connected and the islanded MG operation together with a sensitivity analysis to account for the uncertainty. In the grid-connected mode, our methodology yielded a remarkable 55.30% reduction in the battery's degradation cost and a 27.51% decrease in total expenses compared to the alternative methods with 0.2 C charging/discharging rates. These results underscore the effectiveness of the proposed approach in enhancing both economic and operational performance. Similarly, in the island mode, significant reductions of 41.23% in degradation cost and 10.67% in total cost were observed with respect to the case using 0.2 C charging/discharging rate, underlining the applicability of our methodology across different operational modes. Furthermore, sensitivity analysis, conducted through MCS, provided valuable insights for agricultural MG operators. This analysis emphasized the robustness and adaptability of the proposed methodology, highlighting its ability to navigate uncertainties inherent in energy market dynamics and MG operations. In conclusion, our findings not only demonstrate the substantial economic benefits of incorporating battery degradation modeling into MG scheduling but also underscore the importance of proactive management strategies for sustainable and efficient energy utilization. Accordingly, our proposed methodology offers a pathway towards achieving reliable, cost-effective, and environmentally sustainable energy management practices.

CRediT authorship contribution statement

Vahid Safavi: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Arash Mohammadi Vaniar:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Najmeh Bazmohammadi:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Juan C. Vasquez:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Ozan Keysan:** Writing – review & editing, Supervision, Resources, Project administration, Conceptualization. **Josep M. Guerrero:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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