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Dynamic rolling horizon control approach for a university campus

Yeliz Yoldas[a,*], Selcuk Goren[b], Ahmet Onen[a,c], Taha Selim Ustun[d]

[a] *Department of Electrical–Electronic Engineering, Abdullah Gül University, Kayseri, 38080, Turkey*
[b] *Department of Industrial Engineering, Abdullah Gül University, Kayseri, 38080, Turkey*
[c] *Department of Electrical and Computer Engineering, College of Engineering, Sultan Qaboos University, Al-Khoud, Muscat, 123, Oman*
[d] *Fukushima Renewable Energy Institute, AIST (FREA), National Institute of Advanced Industrial Science and Technology (AIST), Koriyama 963-0298, Japan*

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Abstract

An energy management system based on the rolling horizon control approach has been proposed for the grid-connected dynamic and stochastic microgrid of a university campus in Malta. The aims of the study are to minimize the fuel cost of the diesel generator, minimize the cost of power transfer between the main grid and the micro grid, and minimize the cost of deterioration of the battery to be able to provide optimum economic operation. Since uncertainty in renewable energy sources and load is inevitable, rolling horizon control in the stochastic framework is used to manage uncertainties in the energy management system problem. Both the deterministic and stochastic processes were studied to approve the effectiveness of the algorithm. Also, the results are compared with the Myopic and Mixed Integer Linear Programming algorithms. The results show that the life span of the battery and the associated economic savings are correlated with the SOC values.

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Keywords: Microgrid; Energy management; Rolling horizon control; Model predictive control; Uncertainty; Mixed integer linear programming

1. Introduction

The microgrid (MG) is an effective way to utilize the renewable energy sources (RESs), energy store systems and load demands by providing energy management [1]. Optimization methods are used to find the best solutions to control the MG by ensuring stable and reliable operation [2–4]. Existing studies in the literature are classified as deterministic MG operation or stochastic MG operation [5–7]. In the deterministic operation, RES power output and load demand have not been taken into consideration as uncertainty. Only accurately forecasted variables are considered to achieve the desired objectives. Since unexpected power changes in real time operation, which effect the economic dispatch or ancillary services, cannot be effectively addressed in the deterministic model, the optimal operation of MG cannot be performed properly [8,9]. Stochastic based energy management of MG has also been

* Corresponding author.
E-mail address: yeliz.yoldas@agu.edu.tr (Y. Yoldas).

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studied to tackle the uncertainty problem of RESs and loads. Several approaches are generally based on scenario-based stochastic optimization algorithm [10–12]. Since these scenarios or samples are generated from historical data, the accuracy of the forecasted data in real-time depends on the training scenarios. Therefore, the desired functionality in microgrid energy management may not be performed correctly in the real-time changes. Because high number of scenarios causes computation complexity, and this is unacceptable in most real-world applications. For this reason, scenarios reduction approaches are needed to eliminate the scenarios without loss of critical information [13,14].

The rolling horizon control (RHC) in the literature, also known as model predictive control (MPC), is used to solve different control issues in microgrids [9,15]. RHC can cope with the randomness and intermittence nature of RESs and load demand in real-time microgrid operation. In [16], scenario-based rolling horizon is proposed into two stage stochastic formulation to minimize the operational cost, including the costs of generators and batteries, purchases, penalties, and revenues from electricity exported to the grid. The other paper used a scenario-based model predictive control to minimize the operating cost and total emission of toxic gases [17]. Two stage stochastic approach is formulated as mixed integer linear programming problem (MILP), incorporating model predictive control, and considering load and renewable energy generation uncertainties. The work in [18] proposes a chance constraint MPC for a grid-connected microgrid composed of a gas turbine, battery, and PVs. The authors aimed to minimize the deviation with optimal schedule by taking into consideration uncertainty in the low-level control unit, while high level is used to make economic optimization over a long-time horizon. A 4-level MPC controller was proposed with different electricity market rules in [19]. Also, different kinds of ESS were included in the system to achieve system objectives without considering losses and power flows limits. The study in [20] proposes a fitted rolling horizon control for the stochastic situations, in case of mission or no forecast information. There is no battery degradation consideration, and the network constraints are missing.

This paper suggests a real-time energy management system with RHC for a MG operation under a stochastic and dynamic environment by taking network constraints and battery degradation into account. Stochastic RHC is used to plan the MG operation over 24 h, and with a time interval with 1 h. The aim of the study is to minimize the operational cost, including the battery degradation cost, the energy cost of main grid and the fuel cost of the diesel generator. The suggested algorithm has been tested in a real MG pilot of the Malta College of Arts, Science and Technology (MCAST) by considering the constraints of the network model. Formulation of the MG system including all constraints and limits, has nonlinear equations, with the nonlinearity issue handled through an adaptive grid search algorithm. Through this, the optimum value has been obtained in a very short time. The proposed model is formulated as mixed integer linear programming (MILP) which is solved by the CPLEX solver included in GAMS. The remainder of this paper is organized as follow. Section 2 presents the microgrid structure and formulations used in this study. Rolling horizon approach is described in Section 3. Section 4 gives the simulation environment and result analysis, and Section 5 draws the conclusions.

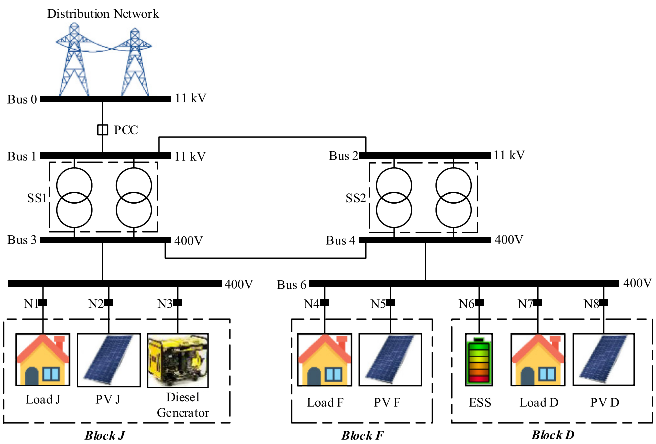

Fig. 1. Microgrid structure.

2. System description

The scheme of the microgrid system is shown in Fig. 1 below. The system is comprised of solar PV arrays (63 kW in total), a diesel generator (300 kW), lithium-ion batteries (300 kWh capacity in total), and loads. This paper assumes that the microgrid operates in grid-connected mode. A finite time horizon of the microgrid operation is considered as $\tau = \{0, \Delta t, 2\Delta t, \ldots T - \Delta t, T\}$, where $\Delta t = 1$ h is the time interval and $T = 24$ h.

2.1. AC power flow

The power flow limits in each branch *ij* is considered as:

$$P_{ij,t} = \frac{\left|V_{i,t}^{2}\right| \cdot \cos\left(\theta_{ij}\right)}{\left|Z_{ij}\right|} - \frac{\left|V_{i,t}\right| \cdot \left|V_{j,t}\right| . \cos\left(\delta_{i,t} - \delta_{j,t} + \theta_{ij}\right)}{\left|Z_{ij}\right|} \tag{1}$$

$$Q_{ij,t} = \frac{\left|V_{i,t}^{2}\right| \cdot \sin\left(\theta_{ij}\right)}{\left|Z_{ij}\right|} - \frac{\left|V_{i,t}\right| \cdot \left|V_{j,t}\right| . \sin\left(\delta_{i,t} - \delta_{j,t} + \theta_{ij}\right)}{\left|Z_{ij}\right|} \tag{2}$$

$$P_{ij,t}^{2} + Q_{ij,t}^{2} \leq \left(S_{ij}^{\max}\right)^{2} \tag{3}$$

where the subscript $i,j \in \{1, 2, \ldots, n\}$ are the indexes of the MG system bus and n is the total number of the bus; $P_{ij,t}$ is the active power flow from bus i to bus j, $Q_{ij,t}$ is the active power flow from bus i to bus j ; $|V_{i,t}|$ is the voltage amplitude at bus i, and $\delta_{i,t}$ is the corresponding voltage angle; $|Z_{ij}|$ is the impedance magnitude of the branch between bus i to bus j and θ_{ij} is the corresponding phase angle.

The power cable transmission capacity limits are also considered as

$$P_{ij,t} \leq P_{ij}^{\max} \tag{4}$$

The voltage amplitude limit is bounded by:

$$V_{i}^{\min} \leq \left|V_{i,t}\right| \leq V_{i}^{\max} \tag{5}$$

where $V_{I}^{\min}$ and $V_{I}^{\max}$ are the minimum/maximum voltage magnitude of bus i respectively.

The power balance equation is also considered as:

$$P_{pv,t} + P_{grid,t} + P_{dg,t} + \left(P_{bat,t}^{d} + P_{bat,t}^{c}\right) = P_{ij,t} + P_{L,t} \tag{6}$$

2.2. Objective function

The objective function of this study is to minimize the daily operational cost and can be expressed as,

$$C_t\left(S_t, a_t\right) = C_{bat,t}\left(S_t, a_t\right) + C_{dg,t}\left(S_t, a_t\right) + C_{grid,t}\left(S_t, a_t\right) \tag{7}$$

Exogenous information vector E_t, includes at time t, which is given by:

$$\hat{E}_t = \left\{\hat{P}_{L,t}, \hat{P}_{pvD,t}, \hat{P}_{pvF,t}, \hat{P}_{pvJ,t}\right\} \tag{8}$$

where $\hat{P}_{L,t}$, $\hat{P}_{pvD,t}$, $\hat{P}_{pvF,t}$, $\hat{P}_{pvJ,t}$ are the available information in the load demand and PV power of each building at time t, respectively.

The exogenous information includes random forecast error (ε), so the exogenous information at time $t + \Delta t$ is given by:

$$E_{t+\Delta t} = \hat{E}_{t+\Delta t} + \varepsilon \tag{9}$$

The available information at time t can be expressed as:

$$I_t = \left(SOC_t, E_t, E_{t+1}, \ldots, E_{t+H}\right) \tag{10}$$

where E_t is the available exogenous information at time t, $E_{t+1:t+H}$ is the future exogenous information with random forecast error between time $t + 1$ to $t + H$.

The decision variables vector x_t of the problem can be given as by:

$$x_t = \left\{P_{bat,t}^{d}, P_{bat,t}^{c}, P_{dg,t}, P_{grid,t}, P_{pvD,t}, P_{pvF,t}, P_{pvJ,t}\right\} \tag{11}$$

where $P_{bat,t}^{d}$, $P_{bat,t}^{c}$ are the discharge and charge power, respectively. $P_{dg,t}$, $P_{grid,t}$ represent the dispatched power of the DG and transferred power between main grid and microgrid, respectively. $P_{pvD,t}$, $P_{pvF,t} P_{pvJ,t}$ represent the injected power by solar panels.

The overall operational cost can be minimized as:

$$V = min E\left[\sum_{t=1}^{T} C\left(t, I_t\right)\right] \tag{12}$$

3. Rolling horizon control approach

Rolling horizon control (RHC) is an iterative and finite-time optimization approach that can be used for real-time/online issues. RHC aims to find the optimal solution for the current time step over sliding window by considering future time steps. RHC can compute the decision variables to fulfil the objective function, while considering exogenous information, future predictions, and constraints. In this way, RHC can adapt to new situations when a disturbance or fault occurs by changing the decision variables according to this new situation [21].

The operation logic of RHC is given in Fig. 2. The future outputs for prediction horizon (H) are predicted based on past and current information and on the predicted future decision variables. These predictions are then used to find the best decision variables applied to the system at the control horizon. At this time, uncertain variables and current state of the MG system are updated. The procedure continues recursively until the final scheduling period of the time [22]. The energy management process of the MG based on RHC and MILP is shown in Fig. 3. The algorithm is initialized by setting horizon size H and time period T. Then the algorithm generates the forecasted data based on exogenous data for horizon H by using RHC and the available information at time t is obtained at step 3. At step 4, the algorithm solves the MILP optimization problem at time t subject to constraints using available information for $t{:}t + H$. After solving the problem, optimal decision variables are obtained and calculated the operational cost for current time step t. This process continues until optimization horizon T.

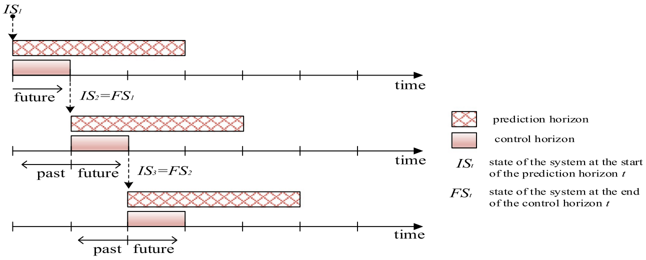

Fig. 2. Rolling horizon framework [22].

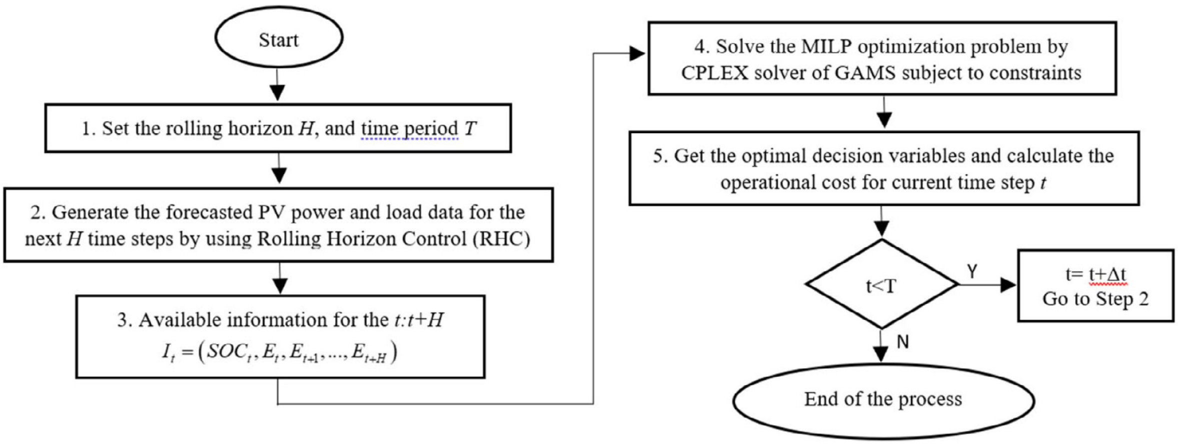

Fig. 3. The flowchart of energy management process.

To cope with the nonlinearity property of power flow equation, adaptive grid search is used to find the minimum and maximum values of power flow between buses by taking into consideration voltage and phase angle limits. In this way, there will not be voltage and phase angle violations. Thus, the computation time is drastically reduced.

4. Simulation environment & numerical analysis

The MG is equipped with a 300 kW/375 kVA DG, 3× 21 kW solar generators, and 150 kW/300 kWh battery as shown in Fig. 1 above. The distribution line parameters are presented in Table 1 below, while the parameters of DG and the battery are given Tables 2 and 3, respectively.

Table 1. Distribution line parameters.

Line		R (mΩ)	X (mΩ)	Line		R (mΩ)	X (mΩ)
From	To			From	To		
Bus 0	Bus 1	129	78.225	Bus 5	N3	3.770	3.989
Bus 1	Bus 2	19.737	11.969	Bus 6	N4	9.048	9.550
Bus 3	Bus 4	11.536	12.208	Bus 6	N5	9.048	9.550
Bus 3	Bus 5	3.770	3.989	Bus 6	N6	4.901	5.186
Bus 4	Bus 6	3.770	3.989	Bus 6	N7	6.786	7.181
Bus 5	N1	3.770	3.989	Bus 6	N8	6.786	7.181
Bus 5	N2	3.770	3.989				

Table 2. Diesel generator parameters.

Item	P_{rated} (kW)	*F1* (L/h/kW)	*F2* (L/h/kW)	k	C_{fuel} (€/L)
Value	300	0.0183	0.22	0.3	1.1

Table 3. Battery parameters.

Parameter	Value	Parameter	Value
E_{max}	300 kWh	P^d_{max}	50 kW
Cycle life	2700 @50% DoD	P^c_{max}	40 kW
$\eta^d \& \eta^c$	0.95	a	−1.24
SOC_{min}	50%	b	7.043
SOC_{max}	100%	Battery cost	220 €/kWh

The stochastic load demand and stochastic PV power supply can be modelled as:

$$P_{L,t+1} = \min\left\{\max\left\{P_{L,t} + \varepsilon^L_{t+1}, P_{L,\min}\right\}, P_{L,\max}\right\} \tag{13}$$

$$P_{pv,t+1} = \min\left\{\max\left\{P_{pv,t} + \varepsilon^{pv}_{t+1}, P_{pv,\min}\right\}, P_{pv,\max}\right\} \tag{14}$$

where ε^L and ε^{pv} is either pseudo normally or uniformly distributed. In this study, $\varepsilon^L \sim \mathcal{N}\left(0, 2^2\right)$ and $\varepsilon^{pv} \sim \mathcal{N}(0, 0.5^2)$. After the probabilities are calculated for load demand and PV power as in (Salas and Powell 2013), the exogenous variables for the next time interval are calculated using equations (13) and (14). The stochastic load demand profile and PV power profile are shown in Fig. 4. The electricity price is represented in Fig. 5 below.

The percentage of optimality (%) is found by the following equation:

$$\%\text{percentage of optimality} = \frac{V^*}{V} \times 100\% \tag{15}$$

where V is the daily operational cost of the MG system using RHC and V^* is the reference (optimal) operational cost obtained from MILP.

4.1. Numerical analysis — deterministic case

In this case, the deterministic dataset of PV power and load demand are used as input at each time interval. To determine the horizon length of the RHC, the optimality percentage is calculated for each time horizon until obtaining the optimum operation cost of the microgrid. When the optimal percentage is obtained as 100% at horizon h, we can observe the optimal value of the system. As shown in Fig. 6, when horizon size h = 0, optimality is 97.84%. It is seen that as the horizon length increases, the optimality reaches 100%. In this study, 100% optimality obtained at h = 11, so with values larger than 11, the optimal value can be achieved. Table 4 shows the comparison of the optimization approaches in terms of daily operational cost and percentage of optimality. The traditional MILP is used to obtain the optimal value.

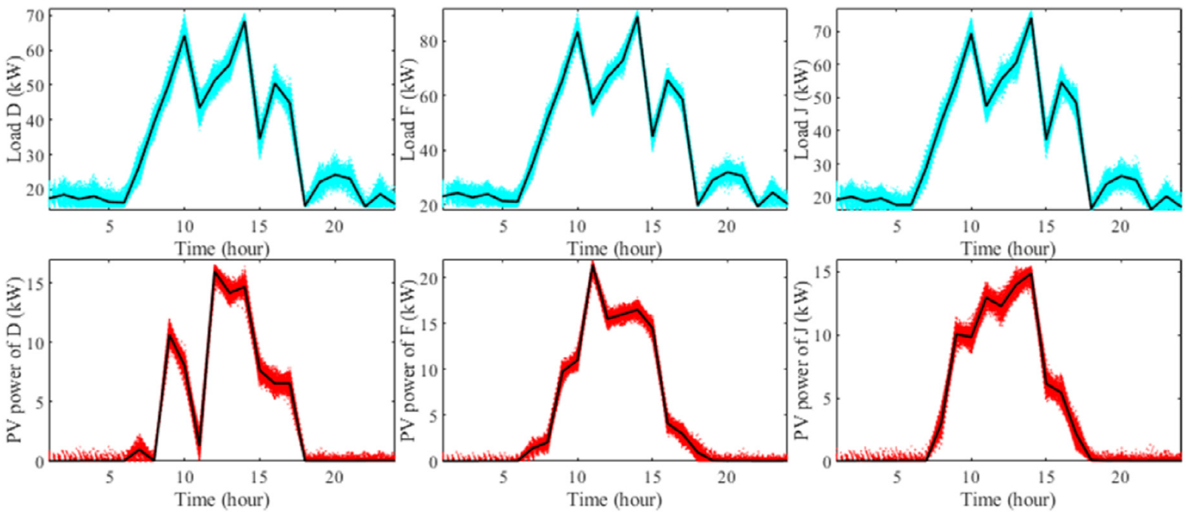

Fig. 4. Load demand and PV power generation for each building in stochastic case.

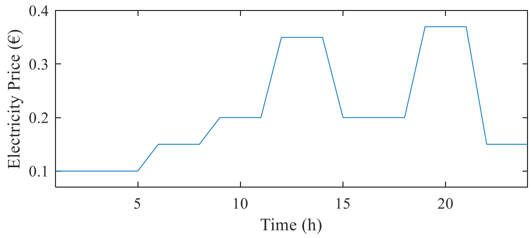

Fig. 5. Electricity price.

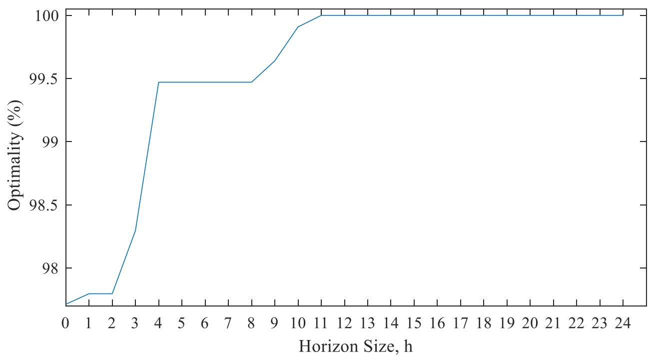

Fig. 6. Percentage of the optimality.

Table 4. Performance comparison for deterministic case.

Approaches	Operational cost (€)	% of optimality
MILP	510.6646	–
RHC	510.6646	100%
Myopic	521.9159	97.84%

4.2. Numerical analysis — stochastic case

In this case, two different probability distribution functions, uniform (U) and normal (N) distributions, are used to make the system stochastic. For example, $U(-1{,}1)$ represents the uniform distributed numbers in the interval $(-1{,}1)$. For the one of the other case $N(0{,}2^2)$, it shows the normal probability distribution where the mean is 0 and the variance is 2. Table 5 shows the comparison of the performance of the RHC and MILP according to different stochastic test problems. Stochastic PV power and load demand are calculated after the noises are obtained thanks to the distributions specified in Table 5. All test problems were conducted when the SOC of the battery was at 75%. For example, for problem no. 1, the daily operational cost of the microgrid system is calculated as €510.4034, while the optimal operating cost obtained from MILP is €510.3115. So, the percentage of optimality is estimated as 99.98%. The table shows that optimality of at least 99.94% is achieved via stochastic RHC.

Table 5. Performance comparison for stochastic case with different noises.

Problem No.	Noise	Daily cost (€)	% of optimality
1	$N(0{,}0.5^2)$	510.4034	99.98%
2	$N(0{,}1.0^2)$	510.4307	99.97%
3	$N(0{,}1.5^2)$	510.4849	99.96%
4	$N(0{,}2.0^2)$	510.6103	99.94%
5	$U(-1{,}1)$	510.3233	99.99%

The power outputs of the battery, DG, PVs, and main grid are presented in Fig. 7. The results show that the battery stores energy when the main electricity price is lowest, between 4–5 h. Then, PV power is dispatched as long as it is available. When the operational cost of DG is cheaper than the electricity price, DG is activated between 12–14 h and 19–21 h. Because DG is operated at 90 kW minimum, power can be bought from the main grid in that situation. Table 6 shows the effect of the battery SOC on the average daily operational cost.

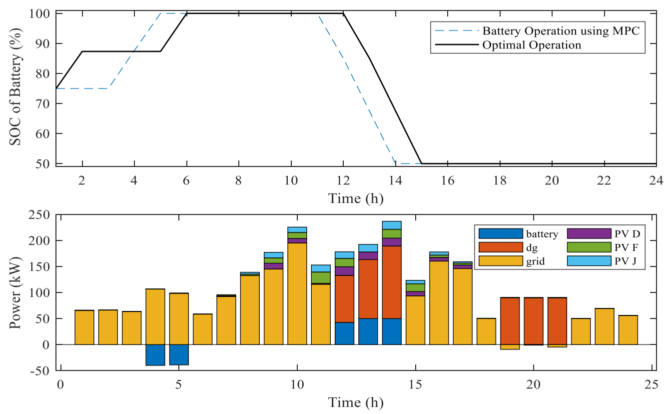

Fig. 7. Behaviour of the SOC value and power outputs of the assets at each time step, respectively.

Table 6. Comparison of results of problem No. 1 with different DoD level.

DoD level (%)	Operational cost (€)	Battery cost, C_{bat} (€)	Battery throughput (kWh)	Maximum battery life (years)
55	509.3745	25.419	144.1437	7.15
50	510.4034	24.407	142.4843	7.39
45	511.9696	21.418	128.2500	8.44
40	513.6191	18.508	114.0000	9.76

Table 6 shows the effect of the DoD of the battery in terms of battery life and daily operational cost in the stochastic case. We assume that the average battery throughput during a year is as stated in Table 6. When the battery is operated at 55% DoD, the daily operational cost and battery throughput are €509.3745 and 144.1437 kWh, respectively. As the level of DoD drops, we can see from the table that the daily operational cost increases to

€513.6191 at 40% DoD and battery throughput falls to 114.00 kWh. In terms of battery life extension, it is assumed that battery life is on average 10 years and the total capital cost of the battery is (300 kWh $\times$ 220 €/kWh) €66,000. So, the calculated cost for each year is €6600. Battery life increases from 7.15 years to 9.76 years, while DoD value decreases from 55% to 40%. So, the So, the capital cost is deferred as 2.61 years, with a net saving of (2.61 $\times$ 6600) €17,226.

5. Conclusion

This study proposes an online energy management of the grid-connected stochastic microgrid operation. In order to achieve optimal economic operation, the rolling horizon control approach is presented by addressing the uncertainties of load demand and PV power generation. To validate the performance of the approach, deterministic and stochastic case studies are conducted. The results demonstrate that the RHC can provide 100% of optimality for the deterministic case and at least 99.94% of optimality for the stochastic case. The stochastic case was conducted with a random forecast error obtained from historical data, with a performance comparison made with MILP. The results show that the RHC approach can perform efficiently even in uncertain circumstances. The formulation integrates the operational costs of each asset in a microgrid, including the degradation cost of a battery, as well as the cost of the main grid and diesel generator. Besides the integration of the network and technical constraints, by adjusting the DoD level of the battery, we can see that the battery life is extended by 2.61 years. Thus, the system's net saving related to its battery is estimated as €17,226.

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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