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Unscented Predictive Control for Battery Energy Storage Systems in Networked Microgrids

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***Abstract*— Controlling batteries State of Charge (SoC) within operational constraints, while minimising the power exchange among microgrids and with the grid, is an important problem to maximise microgrids performance and extend batteries lives. To address this problem, this paper adopts an Unscented Predictive Control (UPC) to optimise the SoC control under uncertain conditions. Based on the model of the NMG and the principle of model predictive control, the design of the SoC control strategy is formulated as an Optimisation Problem (OP) with probability operation conditions. To deal with the latter, the unscented transformation is integrated with predictive control to derive the mean value and variance of system states. A tractable OP for NMGs is then obtained and the effectiveness of the proposed UPC-based SoC control strategy is verified by simulations with different NMG frameworks.**

NOMENCLATURE

Abbreviations

BESS	Battery Energy Storage System
ESS	Energy Storage System
MG	MicroGrid
MPC	Model Predictive Control
NMG	Networked MicroGrid
OP	Optimisation Problem
PC	Predictive Control
PV	PhotoVoltaic
RESs	Renewable Energy Sources
SoC	State of Charge
UG	Utility Grid
UPC	Unscented Predictive Control
UT	Unscented Transformation

Mathematical Definitions

$\mathbb{E}$	Expected operator
$\mathbb{P}$	Probability operator
$\mathcal{N}$	Normal distribution
I	Identity matrix with appropriate dimension
$tr(\cdot)$	The trace a matrix

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I. INTRODUCTION

The Networked Microgrid (NMG) paradigm has emerge thanks to its strong ability to connect Renewable Energy Sources (RESs) and traditional sources [1]. NMGs can provide support to electricity demands and the Utility Grid (UG), while maintaining reliability and self-healing properties under emergencies and unpredictable conditions [2]. Although NMGs come with many advantages, they also introduce some challenges, such as potentially more disturbance and uncertainties than single islanded microgrids that may compromise system's performance, and especially the lifetime of batteries [3]. Hence, one challenge for NMGs is to control the State of Charge (SoC) of batteries so to prevent batteries from being overcharged or undercharged.

As one of the promising tools for NMGs control, Model Predictive Control (MPC) attracts much attention due to its capability of explicitly addressing technical safety and operational constraints [4], [5]. Another reason why MPC has become a successful method is the fact that it can predict future states and perform with a closed-loop policy based on current system state-input pairs. As RESs penetration continues to expand, there is an increasing need for NMGs development and formulating an accurate physical model of possibly complex networks of NMGs is becoming tricky. Traditional MPC may produce large prediction errors when using non-accurate nominal physical models of NMGs [6].

To solve the above-mentioned modelling problem, learning-based Predictive Control (PC) methods are proposed in the literature for NMGs control and management. For instance, Gaussian process modelling is combined with PC in [7], where the photovoltaic output power and the load demand are predicted by the Gaussian process. In [8], an end-to-end neural-network-based PC is proposed to online estimate the uncertain parameters and directly generate the optimal PC actions. Although these learning-based strategies are effective, it is difficult for their black-box mechanism to analyse and guarantee stability conditions and operational and safety constraints.

An alternative method is to design sampling-based PC strategies, such as the particle-based approach presented in [9] and the polynomial chaos expansion method in [10]. These methods can avoid possibly time-consuming and data-eager offline training processes and directly complete the prediction task of PC by collecting real-time samples. However, one common disadvantage of sampling-based methods is that the computational efficiency might be reduced when a large number of samples is required. An interesting sampling-

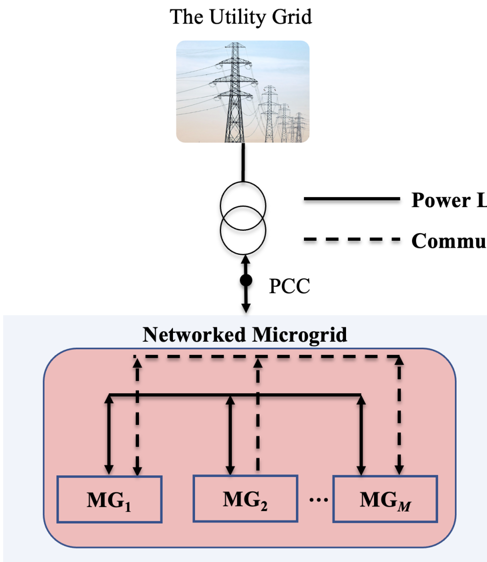

Fig. 1. Networked microgrid diagram with M MGs

based PC method called scenario MPC is proposed in the literature [11]. Nevertheless, scenario MPC focuses on dealing with chance constraints and analysing stability rather than on modelling and prediction uncertainties [12]. Inspired by the unscented Kalman filter [13], [14], Unscented PC (UPC) has been proposed to propagate predictions over a horizon with limited samples [15], [16]. Based on specific nonlinear functions and Sigma points, the Unscented Transformation (UT) can capture the posterior mean and covariance of a random variable accurately to the 3rd order of Taylor series expansion. Therefore, this transformation is easy to design and promising to apply to power system applications.

To the best of the authors' knowledge, this paper is the first work to propose UPC to control the SoC for battery energy storage systems of NMGs. Models of NMGs are first constructed, where the SoC of each MG represents the system states and the system inputs are the power exchange among MGs and the UG. The corresponding Optimisation Problem (OP) with probability operation constraints is then derived. By taking advantage of the properties of the UT, the stochastic OP is transformed into a tractable deterministic problem. Based on this deterministic problem, the UPC-based SoC control method is finally formulated and simulations are carried out to verify the effectiveness of this method.

II. Networked Microgrid Modelling

An NMG composed of M heterogeneous microgrids is considered in this paper. We assume microgrids are connected without any specific structure, and an example is illustrated in Fig. 1. Each MG may include RESs, such as wind and solar PV, batteries, and local loads.

The considered dynamic model for each microgrid $i = 1, 2, ...M$ can be written as [6]:

$$x_i(k+1) = x_i(k) + b_i u_{ij}(k) + c_i d_i(k), \tag{1}$$

where $x_i(k)$ is the SoC of MG i at time step k, $u_{ij}(k)$ is a column vector collecting the values of the power exchanged from MG i to MG $j = 1, 2, ...M$ at time step k, b_i is a row vector that describes the connection among MGs and UG: its elements are defined as $b_{ij} = -b_{ji} = -1, i \neq j$ when MG i and MG j are connected, while $b_{ij} = -b_{ji} = 0$ when MG i and MG j have no connection. c_i is ith battery nominal capacity. $d_i(k)$ is an uncertain power imbalance item which can be influenced by uncertain predicted values of RESs and uncertain loads fluctuation in each MG. In order to meet physical and safety constraints of MGs, such as maximum/minimum power input, maximum/minimum SoC, etc., the following state and input constraints are introduced:

$$x_i(k) \in [x_{min}, x_{max}], \tag{2}$$

$$u_{ij}(k) \in [u_{min}, u_{max}], \tag{3}$$

where x_{min} and x_{max} denote the minimal and maximal values of states, u_{min} and u_{max} denote the minimal and maximal values of inputs. Based on Eqs. (1) - (3), the SoC control problem for the NMG can be solved by designing an optimal control scheme that considers the SoC model (1) while satisfying the constraints (2) and (3).

III. SoC Control Problem for Networked Microgrids

When implementing a PC to MGs, it may be possible to estimate uncertain or unknown parameters by forecasting methods. However, forecasting methods usually have difficulties in adapting in real-time to the changing environment or operation conditions [17], [18], [19]. It is therefore necessary to propose real-time methods able to adapt in real-time and to propagate the disturbance and build the prediction equations in the PC framework. To solve this problem, the UPC scheme is adopted in the following by combining unscented transformation and PC [15], [16].

Based on the mechanism of PC, the following optimisation objective function is given:

$$J(k) = \sum_{p=0}^{N-1} \|X(k+p|k)\|_Q^2 + \|u_{ij}(k+p|k)\|_R^2, \tag{4}$$

where N is the prediction horizon, Q is the state weight matrix and R denotes the input weight matrix , $X(k+p|k) = [x_1(k+p|k), x_2(k+p|k), ..., x_M((k+p|k)]$ denotes the prediction of the state computed at time k for p steps-ahead, $u_{ij}(k+p|k)$ denotes the prediction of the input computed at time k for p steps-ahead. Affected by the power imbalance, the variable $X(k+p|k)$ is a random variable and the objective function (4) can be rewritten as:

$$J(k) = \mathbb{E}\left\{ \sum_{p=0}^{N-1} \|X(k+p|k)\|_Q^2 + \|u_{ij}(k+p|k)\|_R^2 \right\}. \tag{5}$$

Furthermore, to consider the intrinsic stochasticity of the problem, the following optimisation problem (OP) can be derived to control the SoC of each MG in a networked framework:

$$\min J(k). \tag{6}$$

where, inspired by stochastic MPC schemes [20], the following probability operation constraint and the line capacity limitation are given from $p = 0, 1, 2, ..., N-1$:

$$\mathbb{P}\left\{x_{min} \leq x_i(k+p|k) \leq x_{max}\right\} \geq \alpha, \tag{7}$$

$$u_{min} \leq u_{ij}(k+p|k) \leq u_{max}, \tag{8}$$

and where α is the confidence level. However, this OP is intractable due to the uncertainty of the variable $d_i(k+p|k)$. By combining with the UT, a tractable OP is reformulated in what follows.

Firstly, we define the mean and variance of the initial SoC vector $x_i(k)$ as $\mu(k|k)$ and $\Sigma(k|k)$, respectively. Based on these definitions and by exploiting the principle of UT [14], we can approximate the mean and covariance matrix of the prediction sequence $[x_i(k+1|k), x_i(k+2|k), ..., x_M(k+N-1|k)]$ in a recursive matter.

We firstly sample $2n+1$ Sigma points $\sigma^{[l]}$ using the following rules:

$$\begin{aligned}
&\sigma^{[0]} = \mu(k|k) \\
&\sigma^{[l]} = \mu(k|k) + \left(\sqrt{(n+\lambda)\,\Sigma(k|k)}\right)_l \text{ for } l = 1, \ldots, n \\
&\sigma^{[l]} = \mu(k|k) - \left(\sqrt{(n+\lambda)\,\Sigma(k|k)}\right)_l \text{ for } l = n+1, \ldots, 2n
\end{aligned} \tag{9}$$

where $\lambda = a^2(n+b) - n$ and n is the dimension of state $x_i(k)$. The parameters (a, b) determine the quality of approximation and have been analysed in [14]. $(\sqrt{\cdot})_l$ denotes the lth row of the square root matrix. The Sigma points (9) will be used with the following weights

$$\begin{aligned}
w_m^{[0]} &= \frac{\lambda}{n+\lambda} \\
w_c^{[0]} &= \frac{\lambda}{n+\lambda} + \left(1 - a^2 + \beta\right) \\
w_m^{[l]} = w_c^{[l]} &= \frac{1}{2\,(n+\lambda)} \text{ for } l = 1, \ldots, 2n
\end{aligned} \tag{10}$$

where β is a tuning parameter. Based on these Sigma points and weights, the next-step prediction mean $\mu(k+1|k)$ can be obtained as

$$\mu(k+1|k) = \sum_{i=0}^{2n} w_m^{[l]} \bar{\sigma}^{[l]} \tag{11}$$

and the next-step variance $\Sigma(k+1|k)$ as

$$\begin{aligned}
&\Sigma(k+1|k) = \\
&\sum_{j=0}^{2n} w_c^{[l]} \left(\bar{\sigma}^{[l]} - \mu(k+1|k)\right)\left(\bar{\sigma}^{[l]} - \mu(k+1|k)\right)^T + V_0
\end{aligned} \tag{12}$$

where V_0 is the noise covariance of the system disturbance $d_i(k|k)$ and $\bar{\sigma}^{[l]} = \sigma^{[l]} + b_i u_{ij}(k|k)$. By repeating the above process from 0 to $N-1$, the mean and variance of the sequence $x_i(k+p|k)$ can be derived. The expected performance index (5) can be also derived as follows

$$\begin{aligned}
J(k) = \sum_{p=0}^{N-1} &\|\mu(k+p|k)\|_Q^2 + \|u_{ij}(k+p|k)\|_R^2 \\
&+ tr(Q\Sigma(k+p|k))
\end{aligned} \tag{13}$$

To tightening the probability constraint (7), we define $g = [-1, 1]$ and $h = [-x_{min}, x_{max}]$. Then, according to the Chebyshev's inequality [21], the probability state constraint (7) can be approximated as:

$$g^T \mu(k+p|k) + g^T k_p \Sigma(k+p|k) \leq h^T \tag{14}$$

where $k_p = \sqrt{\frac{\alpha}{1-\alpha}}$. Based on the above discussion, we optimally control the SoC of each microgrid under state and input constraints by solving the following OP

$$\min\ (13) \tag{15}$$

$$s.t.\ (8), (14) \tag{16}$$

The resulting UPC strategy is summarised in Algorithm 1.

Algorithm 1 The UPC Strategy:

1: Initialise state $x_i(k)$, input $u_{ij}(k)$, expected value $\mu(k|k)$ and covariance matrix $\Sigma(k|k)$
2: **for** $p = 0, 1, 2, \cdots, N-1$ **do**
3: Sample Sigma points by using Eq. (9)
4: Generate the prediction mean and variance based on Eqs. (9) and (10)
5: Update values by using Eqs. (11) and (12)
6: **end for**
7: Obtain the optimal control sequence by solving OP (15)-(16)
8: Select and apply the first control step $u_{ij}(k)$ for the system (1)

Remark 1: The performance of the proposed method is not affected by the interconnection structure among MGs as long as connectivity is maintained. By increasing the size of the NMG, the computational cost will increase in a nonlinear way in terms of parameters M and n. To reduce this issue, an improved decentralised or distributed architecture is expected to be proposed to decouple parameters M and n in the future work.

IV. Simulation

An example of an NMG composed of three MGs and the UG is introduced to verify the effectiveness of the proposed control method. The connection framework of the considered NMG is shown in Fig. 2. According to this framework, the SoC state vector can be defined as $X(k) = [x_1(k), x_2(k), x_3(k)]^T$ and the power input vector is $u_{ij}(k) = [u_{12}(k), u_{13}(k), u_{23}(k), u_{24}(k)]^T$. The system connection vectors are given as $b_1 = [-1 - 1, 0, 0]$, $b_2 = [1, 0, -1, -1]$, $b_3 = [0, 1, 1, 0]$. By setting the battery nominal

TABLE I
PARAMETERS OF THE PROPOSED METHOD

Name	Value
Prediction horizon length	$N = 10$
The weight matrix of SoC x_i	$Q = 5I$
The weight matrix of power input u_{ij}	$R = I$
The parameters of UT	$a = 0.01, b = 0.05, \beta = 2$
The parameters of constraints	$\alpha = 0.8, x_{min} = 4, x_{max} = 20$
The initial SoC of each microgrid	$x_1 = 6, x_2 = 8, x_3 = 10$

TABLE II
UPC COMPUTATION TIME OF DIFFERENT PREDICTION HORIZON LENGTHS

Prediction Horizon Lengths	UPC Computation Time
$N = 10$	2.165s
$N = 15$	2.563s
$N = 20$	2.838s
$N = 25$	3.246s

capacity of each microgrid to $25kWh$, we can obtain $c_i = \frac{1}{25}$. For simulating this system, we estimate the system (1) by using an openly available dataset in Ref. [22] and the parameters of the proposed UPC are shown in Table I.

Based on these parameters and by setting the reference value for the SoC to $20kWh$, the corresponding results are given in Fig. 3 and Fig. 4. As we can see from Fig. 3 and Fig. 4, all the battery storage devices converge to the reference value within 30 minutes. In Fig. 4, the negative value of u_{24} implies that the UG transmits the power to MG 2. The positive values showing in green, blue and red lines represent the power transmission from MG 1 to MG 2, MG 1 to MG 3 and MG 2 to MG 3, respectively. These three MGs perform well in this networked framework with the connection of the Utility Grid. On the other hand, in order to clearly show the efficiency of the proposed method, Table II reports the computation time under different prediction horizon lengths. From this Table, we can observe that the time increases linearly with the increased prediction horizon lengths. Compared to other sampling methods whose computation time increases exponentially [9], the proposed UPC method benefits from an efficient computation time.

In addition, a comparison with other control schemes is also given. For the sake of simplicity and clarity of presentation, only x_3 and u_{24} are illustrated in Figs. 5 -

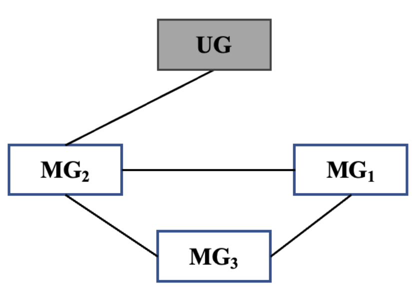

Fig. 2. The connection configuration of the NMG

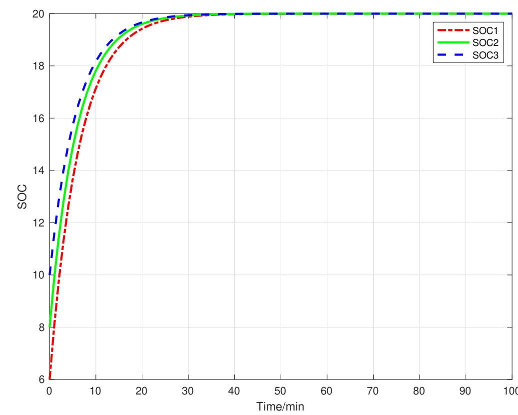

Fig. 3. SoC trajectories in each MG

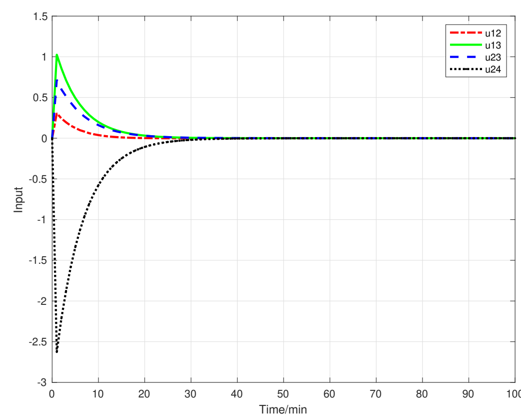

Fig. 4. Power exchange between MGs and the UG

6 by comparing a PID controller, a traditional MPC and the proposed method. It can be seen that all three methods can converge to the reference SoC value, but PID and MPC overcharge the batteries and make SoC trajectories slightly higher than the reference. For the PID control, although the problem may be solved by tuning parameters, the number of parameters needed to be tuned in this problem is 36 due to the dimensions of state and input. Compared with MPC schemes, the tuning process of PID is much more tedious. For the MPC method, it experiences poor performance because it does not consider the impact of the disturbance. On the contrary, the proposed method outperforms both methodologies showing in Fig. 6.

The PID, MPC and UPC are also deployed on a different NMG system that consists of 10 MGs. The connection is shown in Fig. 7 and the trajectories of 10 SOCs are depicted in Figs. 8 - 10. As can be seen from Fig. 8, PID performs worse when enlarging the NMG network. This is because tuning corresponding parameters is the key to PID. However, there are 360 PID parameters in this NMG and it is difficult to tune such a number of parameters. By observing Figs. 9 and 10, we can see that the NMG is trying to continuously

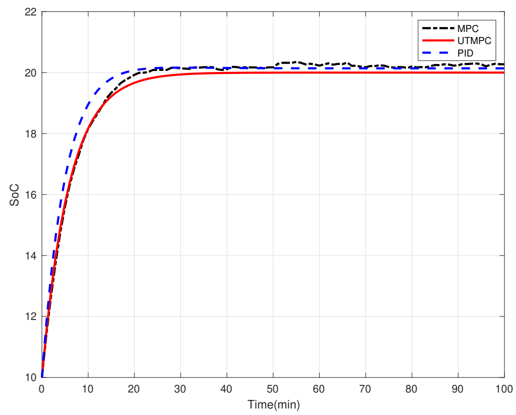

Fig. 5. SoC trajectories with different control schemes

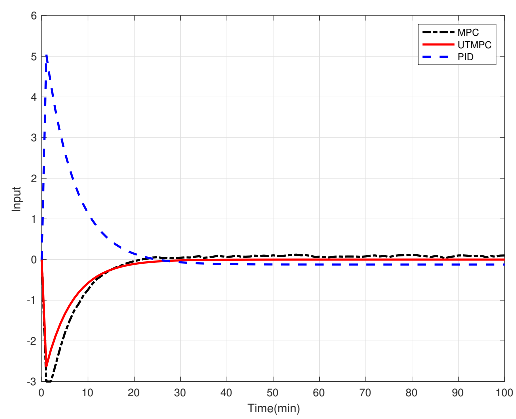

Fig. 6. Power exchange between MG 2 and the UG 4 with different control schemes

approach the expected value in an oscillating form under the usage of the traditional MPC. This phenomenon implies that the traditional MPC is affected by the disturbances even more when the number of MGs increases, resulting in continuous fluctuations in SOC. By contrary, the proposed method can drive the NMG to converge to the desired SOC.

V. Conclusion

To control batteries SoC and minimise the power exchange among each microgrid, an unscented predictive control was proposed in this paper. Firstly, unscented transformation was used to propagate the power imbalance caused by RESs and their forecasting values. Besides, a modified optimisation problem was formulated by considering the mean and variance of the SoC. By solving this optimisation problem under operation and safety constraints, optimal operation signals were obtained. The effectiveness of the proposed method was verified in a simulation environment considering different frameworks of NMGs. As a future work, we would like to consider more complex and larger networks integrating the energy storage control with the other aspects of the NMG control and the robustness of the proposed method

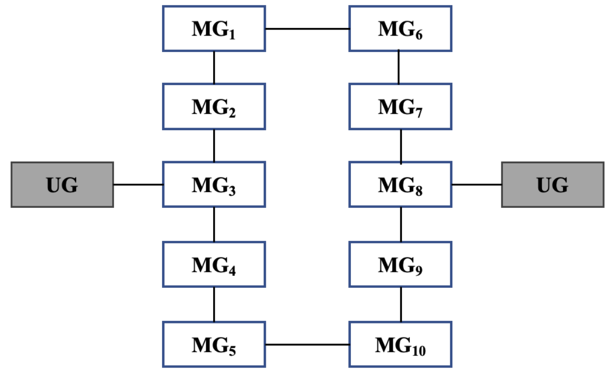

Fig. 7. The connection configuration with 10 MGs

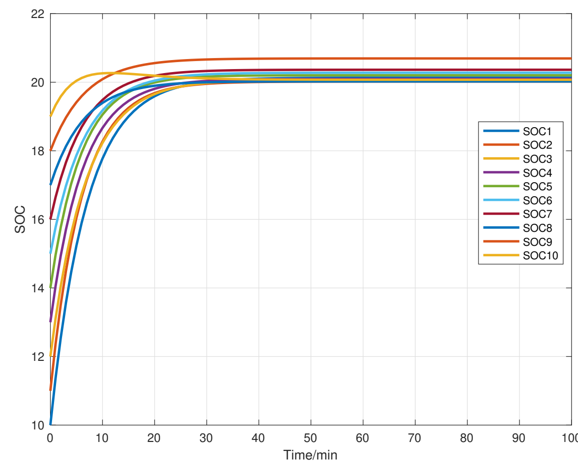

Fig. 8. 10 SoC trajectories with PID method

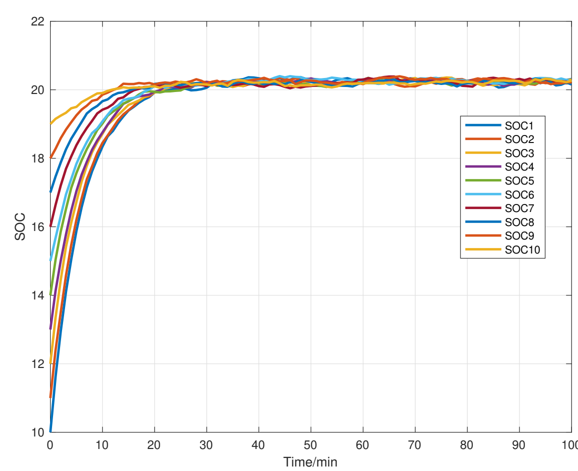

Fig. 9. 10 SoC trajectories with general MPC method

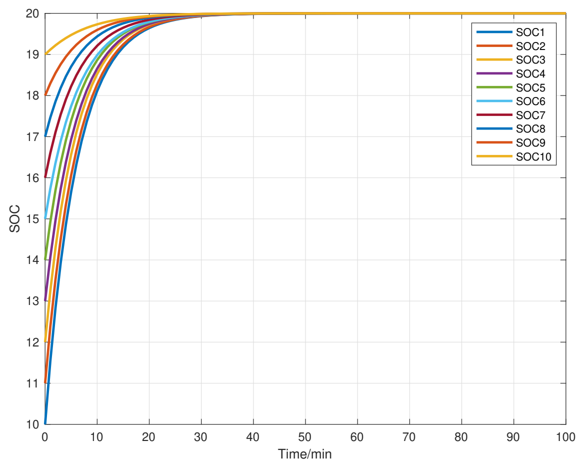

Fig. 10. 10 SoC trajectories with the proposed method

to parameter uncertainties and external disturbances will be explored.

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