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Operation Management of More-Electric Aircraft Using Two-stage Stochastic Model Predictive Control

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Keywords

«Electrified aircraft», «Energy management», «Model Predictive Control», «Optimization», «Load scheduling».

Abstract

This paper proposes a two-stage stochastic model predictive control (SMPC) for the operation management of more electric aircraft (MEA). The goal is to minimize load shedding and switching activities in the system, considering the uncertainty of load profile, while optimally charging/discharging the battery-based energy storage system (BESS). In addition, several performance evaluation criteria are introduced to evaluate the effectiveness of the proposed approach. According to the results obtained in 50 random scenarios, SMPC leads to less load-shedding time, higher stored energy levels, and lower uncertainty compensation costs compared to its deterministic counterpart.

Introduction

The aircraft industry is responsible for providing fast, reliable, and comfortable flights. However, it contributes to approximately 2.5% of global human-induced CO2 emissions. Environmental issues have been among the main concerns in the developing aviation industry in recent years. In this regard, the concept of more electric aircraft (MEA) is attracting a lot of attention for developing new aircraft systems. In MEA, traditional hydraulic and pneumatic systems are replaced with electrical systems, which results in reducing fuel consumption while improving the system's efficiency and dynamic response [1],[2],[3]. However, to achieve these goals, efficient control and operation management systems for the onboard electrical power system (EPS) are required.

The EPS in MEA includes diesel generators as the main source of power as well as several energy storage systems (ESS) and loads with different priorities. There are a variety of loads in MEA, such as the ice protection unit, flight and environment control systems, galley and entertainment loads, and lights, that can be classified as high, mid., and low priority loads based on their criticality [4]. To preserve flight safety and fuel efficiency, the operation of different system components with their specific characteristics must be coordinated while satisfying several technical and operational constraints. Hence, power management of the EPS is a challenging task. Although there are several techniques to predict the power demand of different power consumption units, uncertainty is an inseparable part of EPS loads stemming from their fluctuating nature. Thus, appropriate uncertainty-handling techniques are required.

Operation management of the EPS of MEA has been attracting the attention of academia in recent years. In [5], a stochastic optimization problem is formulated to smooth the output power of the main generators in an MEA using a hybrid ESS (HESS) in an online manner. Lyapunov optimization approach is used to solve the optimization problem. Different HESS are also evaluated. A power allocation strategy for MEA to minimize load shedding is proposed in [6]. Battery scheduling is performed to confine generators to work within their optimal operating range. A distributed model predictive control based on the alternating direction method of multipliers (ADMM) is proposed in [7]. Different update rates are considered for engine and power subsystems. In [8], a stochastic optimal control strategy is designed for aircraft EPS. Chance-constrained model predictive control (MPC) is used to mitigate the uncertainty in inputs and dynamics of the system. Normal probability distribution (PDF) is used for representing the uncertainty in the output power source as well as sheddable and non-sheddable loads while the failure probability of system contactors is modeled as a Bernoulli random variable. In [9], coordinated control of the gas turbine engine and generators of an MEA is studied while enforcing constraints. A Markov chain model is used to construct scenario trees of the possible mission pathways and scenario-based MPC is applied to the problem to minimize the system cost.

This paper explores the potential of two-stage stochastic MPC (SMPC) in the operational management of MEA and mitigating the volatility of loads. The proposed operational management strategy adaptively splits power among different sources of power, including the main generator and the battery storage system.

The rest of this paper is organized in several sections including Problem formulation, Two-stage SMPC, Simulation Results, and Conclusion.

Problem Formulation

In this section, the integrated power management problem of the EPS is presented. Fig. 1 shows the general architecture of the EPS of an MEA. The aircraft EPS studied in this paper is composed of a main engine, a battery-based ESS (BESS), and loads. It is assumed that there are both sheddable and non-sheddable loads in the system. The sheddable loads are further classified as high-priority and low-priority loads as can be seen in Fig. 1. The main goal is to minimize load shedding and switching activities in the system, as well as maintain sufficient energy in the BESS. Decision variables include generators' output power, batteries charging/discharging power, and load connection/disconnection following their priorities. The operation management problem can be mathematically formulated as an optimization model to provide optimized values for the decision variables. The abovementioned control goals are formulated by an objective function, with a set of constraints related to EPS dynamics and several technical and operational requirements. In this paper, the optimization problem is formulated as a Mixed-Integer-Linear-Programming (MILP) model, which can be solved effectively by available solvers, such as CPLEX.

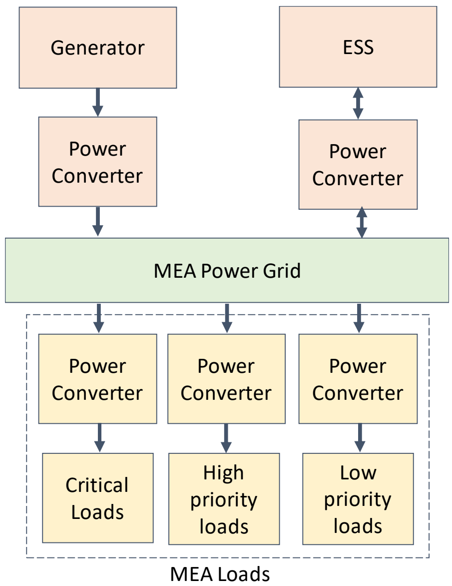


Fig. 1 General architecture of EPS of MEA

Nomenclature

The main symbols in the EPS model are introduced in Table I.

Table I: Nomenclature

Parameters	
T_s	Sampling time [s]
k	Time interval ($k \in \mathbb{Z}_{\geq 0}$)

η_{ch} / η_{disch}	BESS charging/discharging efficiency
B_{cap}	BESS capacity [kWh]
P_{ch}^{max}, P_{disch}^{max}	BESS maximum charging/discharging power [kW]
SOC^{max}/ SOC^{min}	Upper/lower bounds of the BESS SOC target range
P_{in}^{max}	Maximum input power from the generator [kW]
$P_{Li}^{shed}(k)$	The *i*th non-critical load power [kW]
γ_{Li}	The priority of the *i*th non-critical load
N_{Li}	Total number of non-critical loads
$P_{Li}^{nonshed}(k)$	The *i*th critical load power [kW]
Continues Variables	
$P_{in}(k)$	Input power from the generator [kW]
$P_{ch/disch}(k)$	BESS charging/discharging power [kW]
$P_{batt}(k)$	BESS net power [kW]
$SOC(k)$	BESS state of charge
Binary Variables	
$S_{Li}(k)$	Contactor connection status of the *i*th non-critical load
$\zeta_{ch/disch}(k)$	Indicator for charging/discharging the BESS

Constraints

The four groups of constraints considered in the energy management system are formulated as follows.

Power balance: Following Kirchhoff's Current Law for a given voltage, the total power received from the power sources equals the power consumption of the loads at each time instant k, assuming no losses within the power grid transmission:

$$P_{in}(k) + P_{disch}(k) - P_{ch}(k) - \sum_i S_{Li}(k)P_{Li}^{shed} - \sum_j P_{Lj}^{nonshed} = 0 \tag{1}$$

ESS dynamic model: The state of charge (SOC) indicates the level of charge of a BESS relative to its capacity. The SOC can be calculated from the charging/discharging power over time.

$$SOC(k+1) = SOC(k) + T_s \cdot \eta_{ch} \cdot \frac{P_{ch}(k)}{B_{cap}} - T_s \cdot \frac{P_{disch}(k)}{B_{cap} \times \eta_{disch}} \tag{2}$$

The SOC limits are enforced by the following equation, representing the target range of SOC to ensure flight safety.

$$SOC^{min} \leq SOC(k) \leq SOC^{max} \tag{3}$$

BESS charging/discharging mode: The battery can be either charged or discharged within the power limitation in the EPS. Therefore, two binary indicators are introduced to represent different modes selected during the flight:

$$\begin{gathered} \zeta_{ch}(k) + \zeta_{disch}(k) = 1, \zeta_{ch}(k), \zeta_{disch}(k) \in \{0,1\} \\ 0 \leq P_{ch}(k) \leq \zeta_{ch}(k) \cdot P_{ch}^{max} \\ 0 \leq P_{disch}(k) \leq \zeta_{disch}(k) \cdot P_{disch}^{max} \end{gathered} \tag{4}$$

Generator power limitation: The input power from the generator cannot exceed its upper bound, considering the rated power of the generator:

$$0 \leq P_{in}(k) \leq P_{in}^{max} \tag{5}$$

Objective function

As mentioned above, the operation management of the studied EPS aims at 1) minimizing the total time for which loads are shed following the load priorities, which means high-priority loads are less shed than low-priority loads; 2) minimizing the switching activities caused by load shedding/connecting to reduce transient issues in the system; 3) avoiding BESS discharging and encouraging its charging to improve the resilience of the EPS in scenarios with energy shortage.

A multi-objective function in (6) is consequently proposed combining objectives in (7)-(9) for each target by adding weighting factors w_s, w_δ, and w_{bat}. In (7), the load shedding is minimized by penalizing the shedding of loads with the load priorities. Equation (8) indicates the change in load connections for each time interval is minimized. The BESS charging power is maximized while it's discharging power is minimized in (9). In addition, the charging speed of the battery can be changed by adopting different weighting factors for charging/discharging, i.e., w_{ch} and w_{disch}, respectively [4].

$$Obj(k) = w_s f(S_{Li}) + w_\delta f(\delta_{Li}) + w_{bat} f(P_{bat}) \quad (6)$$

$$f(S_{Li}) = \frac{\sum_{i=1}^{N_{Li}} \gamma_{Li}(1-S_{Li}(k))}{\sum_{i=1}^{N_{Li}} \gamma_{Li}} \quad (7)$$

$$f(\delta_{Li}) = \frac{\sum_{i=1}^{N_{Li}} |S_{Li}(k+1)-S_{Li}(k)|}{N_{Li}} \quad (8)$$

$$f(P_{bat}) = w_{disch} \frac{P_{disch}(k)}{P_{disch}^{max}} - w_{ch} \frac{P_{ch}(k)}{P_{ch}^{max}} \quad (9)$$

Two-Stage Stochastic Model Predictive Control

Model predictive control (MPC) is a widely used control technique for dynamic systems with constraints on state and input variables. The ability of MPC to handle multi-input multi-output systems and operational constraints, as well as accounting for future changes in the system, has made it a successful control technique for practical applications [10]. In MPC, using the dynamical equations of the system, the optimal control sequence over the desired control horizon is derived by minimizing an objective function. Although the receding horizon strategy of MPC and accounting for future system conditions make MPC an efficient solution strategy for many applications, appropriate uncertainty handling techniques are required in cases with considerable sources of uncertainty. In this regard, robust MPC [11], chance-constrained SMPC [12], and scenario-based SMPC [13] have been considered in many applications.

In the two-stage SMPC with resource variables, there are two types of decision variables, namely the first-stage, and the second-stage decision variables. The first-stage decision variables are decided before the realization of uncertainty while the second-stage variables are considered resource variables and are determined after the realization of uncertainty [14]. The first-stage decision variables are determined in a way that the total system cost including the operation cost and the expected penalty cost from possible constraint violation is minimized. To this end, two slack variables $r^+$and $r^-$are introduced to the problem as second-stage decision variables which represent corrective actions in case of any constraint violation. Since constraint violation can only be determined after the realization of uncertainty, different realizations of uncertain variables are considered as scenarios associated with an occurrence probability π. Considering S different scenarios for uncertain variable realization with a probability of $\pi_s, s\epsilon 1, \cdots, S$, and slack variables $r_s^+$and r_s^-, the two-stage SMPC problem at each time instant t can be formulated as follows:

$$\underset{u(t,\cdots,t+N-1)}{\text{Min}} \sum_{k=0}^{N-1} f(u(t+k)) + \sum_{k=0}^{N-1} \sum_{s=1}^{S} \pi_j \left(p^+ r_j^+(t+k) + p^- r_j^-(t+k)\right) \quad (10)$$

$$g(u(t+k)) \le 0 \quad (11)$$

$$h(u(t+k), \delta_s(t+k)) \le r_s^+(t+k) \quad (12)$$

$$-(h(u(t+k), \delta_s(t+k))) \le r_s^-(t+k) \quad (13)$$

$$u(t+k) \in U \quad (14)$$

$$r_s^+(t+k), r_s^-(t+k) \ge 0 \quad (15)$$

$$k \in 0, \cdots, N-1, s \in 1, \cdots, S$$

In (10), the first term ($f(u)$) is the first stage cost representing the operation cost of the system while the second term shows the expected penalty cost over the prediction horizon N. In addition, p^+ and p^- represent penalty coefficients, and u is the set of first-stage decision variables while δ contains uncertain parameters. Equation (11) represents the set of deterministic constraints that are not dependent on the uncertain parameter, while (12) and (13) show the modified balance constraint in the form of $h\big(u(t), \delta(t)\big) = 0$ that cannot be guaranteed due to the presence of uncertainty and is thereby adjusted with the introduction of slack variables. Exploiting the available knowledge of uncertain variables, a probability distribution function (PDF) is approximated and used to generate random scenarios.

Two-stage stochastic MPC of MEA EPS

In this paper, the power demand of each load is considered as a random variable complying with a normal PDF with a mean value equal to the predicted demand and a standard deviation (SD). Due to the presence of random load demand in the system, the satisfaction of the power balance equation in (1) cannot be guaranteed before the realization of uncertainty. Thereby, applying the two-stage stochastic MPC with resource variables introduced in the previous section, the operation management problem of MEA EPS at each time instant t is formulated as a stochastic optimization problem as follows:

$$\text{Min} \quad F(t) = \sum_{k=0}^{N-1} Obj(t+k) + \sum_{k=0}^{N-1} \sum_{s=1}^{S} \pi_s (p_s^+ r_s^+(t+k) + p_s^- r_s^-(t+k)) \tag{16}$$

s.t. (2)-(5), (7)-(9)

$$P_{in}(t+k) + P_{disch}(t+k) - P_{ch}(t+k) - \sum_i S_{Li}(t+k) P_{Li_s}^{shed}(t+k) - \sum_j P_{Lj_s}^{nonshed}(t+k) \le r_s^+(t+k) \tag{17}$$

$$-\left(P_{in}(t+k) + P_{disch}(t+k) - P_{ch}(t+k) - \sum_i S_{Li}(t+k) P_{Li_s}^{shed}(t+k) - \sum_j P_{Lj_s}^{nonshed}(t+k)\right) \le r_s^-(t+k) \tag{18}$$

$$r_s^+(t+k), r_s^-(t+k) \ge 0 \tag{19}$$

$$k \in 0, \cdots, N-1, s \in 1, \cdots, S$$

In (17)-(19), $P_{Li\_s}^{shed}(t+k)$ indicates the demand power of the sheddable load Li in scenario s. In addition, $P_{Lj\_s}^{nonshed}(t+k)$ is the power demand of the non-sheddable load Li in scenario s at time instant $t+k$ while being at t. p^+ and p^- represent penalty coefficients to penalize any power deviation due to uncertain load variations.

Simulation Results

In this section, to evaluate the effectiveness of the proposed stochastic energy management strategy, an online simulation is conducted to compare the results of SMPC and deterministic MPC (DMPC). Load profiles illustrated in Fig. 2 are adopted for simulation purposes. In this figure, the forecasted power demand of each type of load is represented by a blue dashed line (Load Pre), which is also considered the mean load value in SMPC. In DMPC, as load uncertainty is not considered, optimizations are performed for predicted loads. In SMPC, 50 random scenarios (S=50) are generated at each time instant k for each type of load following a normal PDF, where an SD of 1% is assumed around the mean value. The maximum and minimum load power of all scenarios are represented in Fig. 2 (Load max and Load min, respectively).

To compare the online performance of the SMPC and DMPC, a real-time load profile, represented by a red line (Load Real) in Fig. 2, is assumed. It is worth noting that, this real-time load profile follows a normal PDF as well. The performance of SMPC and DMPC for achieving the control targets is compared based on this real-time load profile. Moreover, slack variables r_s^- and r_s^+ indicate the potential power unbalance requiring compensation in real-time control. In this paper, it is assumed that the compensation is realized by the generator, which is associated with a high penalty factor for exceeding the assumed maximum power P_{in}^{max}. This is named the compensation cost for the generator.

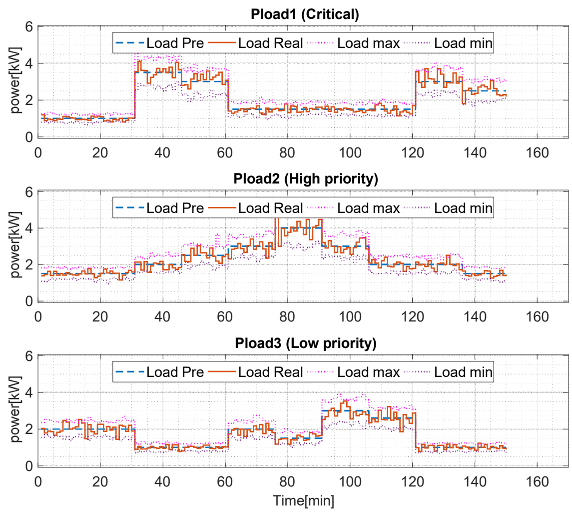


Fig. 2 Load profiles

Evaluation for control targets

Fig. 3 and Fig. 4 represent the load shedding and SOC results when adopting the proposed SMPC and DMPC methods. From Fig. 3, SMPC can be seen to lead to less load-shedding time compared to DMPC. During 120-132 min, the low-priority load is connected to the system in the case of SMPC, while in the DMPC case, it is shed. In addition, applying SMPC leads to higher SOC levels, close to the upper bound, compared to the SOC results obtained from DMPC. Evaluation functions $g(S_{Li})$, $g(\delta_{Li})$, $g(SOC)$, and $g(Obj)$ are proposed in (20)-(23) to calculate the operating costs including load shedding, switching activities, stored energy, and overall operating cost. In (20)-(23), T is the total time steps during all flight stages. $g(S_{Li})$ in (20) indicates the average load shedding, $g(\delta_{Li})$ in (21) is the total switching activities during the flight, and $g(SOC)$ in (22) evaluates the average of the difference of SOC with its upper bound. The overall operating cost combines the evaluation functions in (20)-(22) weighted by v_s, v_δ, and v_{SOC} as presented in (23). In this paper, the weights for each cost term are equally set to 1. For all evaluation functions, less value indicates better performance in achieving the control targets.

$$g(S_{Li}) = \frac{\sum_{k=0}^{T}\sum_{i=1}^{N_{Li}}\gamma_{Li}(1-S_{Li}(k))}{T\sum_{i=1}^{N_{Li}}\gamma_{Li}} \quad (20)$$

$$g(\delta_{Li}) = \frac{\sum_{k=0}^{T-1}\sum_{i=1}^{N_{Li}}|S_{Li}(k+1)-S_{Li}(k)|}{T} \quad (21)$$

$$g(SOC) = \frac{\sum_{k=0}^{T}|HI - SOC(k)|}{T} \quad (22)$$

$$g(Obj) = v_s f(S_{Li}) + v_\delta f(\delta_{Li}) + v_{SOC}\, g(SOC) \quad (23)$$

Table II presents the evaluation of the objectives when adopting SMPC and DMPC methods for the online simulation. Compared to the DMPC strategy, the SMPC method improves the performance in load shedding and SOC level by 5.45% and 16.97%, respectively. This leads to the reduction of the overall operating cost by 9.4% when adopting the SMPC method. This indicates that when the uncertainty is not considered, the imprecise load prediction can result in poor performance for the control targets, while the proposed SMPC method can avoid this drawback by explicitly considering the load uncertainty in planning the operating strategy.

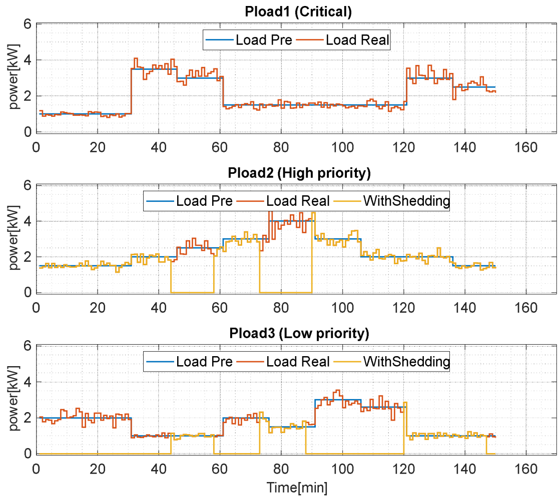
Table II: Evaluation of the control targets

Item	$g(S_{Li})$	$g(\delta_{Li})$	$g(SOC)$	$g(Obj)$
SMPC	0.35	0.07	0.23	0.64
DMPC	0.37	0.07	0.28	0.71
Reduction Percentage (%)(1)	-5.45	0	-16.97	-9.40

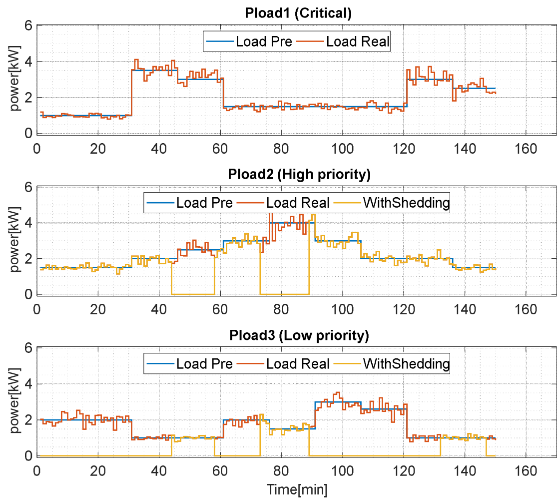
(1) Reduction Percentage: the reduced percentage when comparing the results of SMPC with DMPC

Evaluation for compensation

In this paper, it is assumed that the generator can compensate for the deviations of power unbalance, i.e., the slack values of $r_s^+ + r_s^-$. However, this leads to a compensation cost with a high penalty in addition to the operating cost.

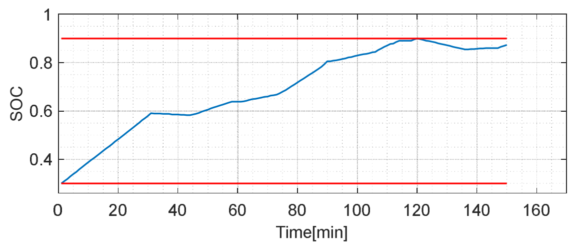


(a) SMPC

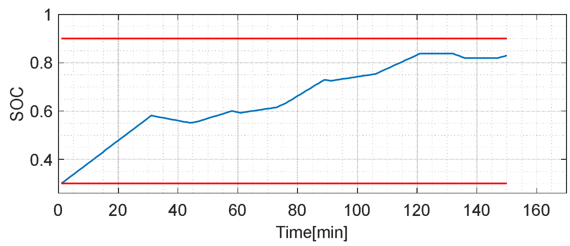


(b) DMPC

Fig. 3 Load shedding/connecting results for SMPC and DMPC



(a) SMPC

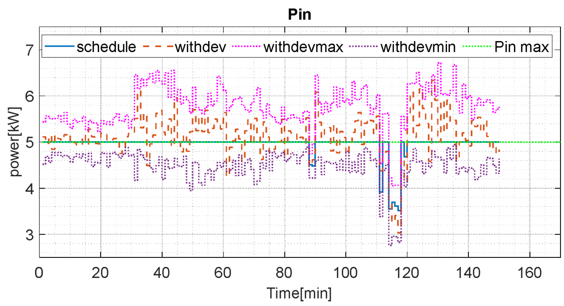


(b) DMPC

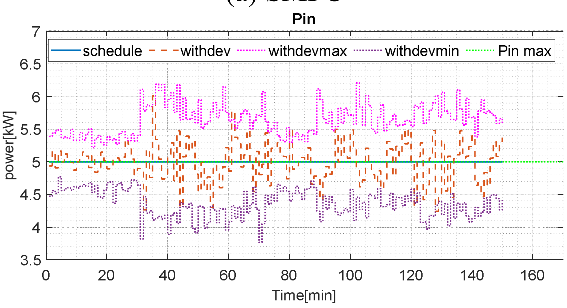
Fig. 4 SOC results for SMPC and DMPC

It is also assumed that the battery power follows the scheduled power from the SMPC and DMPC strategies. When the DMPC strategy is applied to the EPS, the BESS power is allocated without considering load uncertainty. Consequently, the generator compensates for all the deviations between the predicted and real-time load power. In contrast, the SMPC method schedules the BESS power considering the uncertainty, thereby less power deviation is required to be compensated for by the generator.

In Fig. 5, the power allocated to the generators is presented. The generator power scheduled by SMPC and DMPC strategies are illustrated by a blue line (schedule) in Fig. 5 (a) and (b), respectively. To compensate for the real-time deviations between the scheduled power supply and the power consumption, the generator scheduled power should be increased with the real-time deviation, presented by the red dashed line (withdev) in Fig. 5. In addition, in the adopted 50 uncertainty scenarios, the generator power for compensating the maximum and minimum deviations is presented in Fig. 5 (withdevmax and withdevmin respectively).



(a) SMPC



(b) DMPC

Fig. 5 Input power from the generator

To compare the compensation cost when adopting the SMPC and DMPC methods, the evaluation functions $g(r)$ and $g(CV)$ are proposed in (24)-(25). $g(r)$ indicates the average deviations required to be compensated for by the generator in all scenarios and flight stages. $g(CV)$ indicates the average power exceeding the assumed power limitation P_{in}^{max} in all scenarios and flight stages.

$$g(r) = \frac{\sum_{s=1}^{S}\sum_{k=0}^{T} r_s^{+}(k) + r_s^{-}(k)}{T \cdot S} \qquad (24)$$

$$g(CV) = \frac{\sum_{s=1}^{S}\sum_{k\in\{P_{in}>P_{in}^{max}\}}^{T-1} (P_{in}(k) - P_{in}^{max})}{T \cdot S} \qquad (25)$$

Table III presents the evaluation results of the deviation compensation costs when adopting SMPC and DMPC strategies for both real-time load and 50 uncertain load scenarios. It can be observed that by adopting the SMPC method, all the compensation costs for different scenarios are reduced.

Table III: Evaluation of compensation costs

	Real-time load case		50 load scenarios	
	$g(r)$	$g(CV)$	$g(r)$	$g(CV)$
SMPC	0.3056	0.1422	0.2842	0.0436
DMPC	0.5108	0.1513	0.4716	0.1480
Reduced Percentage	-40.17%	-6.01%	-39.74%	-70.54%

Conclusion

In this paper, the operation management problem of the electric power system of more electric aircraft is formulated in the framework of two-stage SMPC. The studied electric system comprises a main generator, a battery-based energy storage system as well as critical and non-critical loads. Load variation during different flight stages is considered the main source of uncertainty in the system, which is mitigated by the proposed stochastic framework. Simulation results illustrate the effectiveness of the proposed approach with respect to the deterministic model predictive control in minimizing load shedding, switching activities, and maintaining a high state of charge levels in the batteries.

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