Energy Scheduling of Wind-Storage Systems Using Stochastic and Robust Optimization

Lysandros Tziovani, Lenos Hadjidemetriou, Stelios Timotheou
KIOS Research and Innovation Center of Excellence and Department of Electrical and Computer Engineering
University of Cyprus
Nicosia, Cyprus
{ltziov01, lhadji02, stimo}@ucy.ac.cy

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***Abstract*—Energy storage systems (ESSs) is an emerging technology that enables increased and effective penetration of renewable energy sources into power systems. ESSs integrated in wind power plants can reduce power generation imbalances, occurring due to the deviation of day-ahead forecasted and actual wind generation. This work develops two-stage scenario-based stochastic and robust optimization schemes for the day-ahead energy scheduling of combined wind-storage systems, considering wind power uncertainty and the power balancing capability of the ESS. The set of scenarios used in the optimization schemes is appropriately selected from historical data of a real wind farm to closely match the day-ahead forecasted power production. Simulation results demonstrate the superiority of the stochastic and robust optimization schemes in terms of producer profits and power imbalances compared to the corresponding deterministic optimization scheme. The results also highlight that the two schemes offer a different trade-off between profits and power imbalances, making the stochastic and robust schemes more desirable for the producer and system operator, respectively.**

***Index Terms*—Electricity markets, energy storage systems, robust optimization, stochastic optimization, wind power plants.**

I. Introduction

Wind energy is one of the fastest-growing renewable technologies with its total power capacity worldwide increasing from 177 to 732 GW over the decade 2010-2020 [1]. The increasing penetration of wind energy into the power system is expected to continue, as the European Union has set a target to become climate-neutral by 2050 [2]. One challenge that needs to be overcome to achieve this target regards the power imbalance between day-ahead scheduled and actual generation due to wind generation uncertainty [3]. To reduce high power imbalances, wind power plants (WPPs) are penalized in the electricity markets when deviations occur between day-ahead scheduled and actual power generation [3]. This incentivizes WPPs to provide more accurate power production schedules to the day-ahead market. Towards this direction, a stochastic optimization model minimizing the expected costs for power imbalances of a WPP is formulated in [4]. Since wind power predictions are never perfect and thus full elimination of power imbalances is not realistic, in [5] the power imbalances are penalized when they exceed an allowed imbalance band around the scheduled power production.

Power imbalances can also be reduced using energy storage systems (ESSs) integrated in the WPPs. Specifically, ESSs can be charged or discharged during the real-time operation of the system to reduce power imbalances and the associated penalty costs [6]. Scenario-based stochastic optimization schemes to maximize the expected profit of wind and pumped-storage systems by scheduling the produced power submitted to the market are formulated in [3], [7]. Specifically, 21 wind production estimations are used in [3] to represent scenario curves, while the scenarios used in [7] are generated based on wind power forecast errors. Instead of using scenarios, a stochastic optimization scheme that adopt a probabilistic distribution to model wind power uncertainty is proposed in [8], considering a battery energy storage system (BESS). Robust optimization schemes to maximize the profits of wind-ESS systems by characterizing the wind power uncertainty using an uncertainty set are proposed in [9], [10], where a compressed air energy storage is considered in [9]. The main disadvantage of [3], [4], [7]–[10] is the utilization of complementarity constraints to eliminate the simultaneous charging/discharging power of ESSs, resulting in mixed-integer optimization problems which are hard to solve, and require the usage of costly commercial optimization tools.

This work develops two-stage scenario-based stochastic and robust optimization schemes to define the scheduled power that is submitted to the day-ahead market for wind-BESS systems by maximizing the expected WPP profit. The developed schemes maximize the revenue of selling power to the grid and minimize the penalty cost from power imbalances that exceed an allowed imbalance band around the scheduled power of the wind-storage system. Towards this direction, power imbalances are considered by representing the wind power uncertainty in the real-time market using a set of scenarios that is appropriately selected from historical data of a real WPP to closely match the day-ahead forecasted production. Moreover, the weighting value of each scenario in the stochastic scheme is defined according to the closeness-of-fit between the associated scenario curve and the forecasted power production curve. A relaxed BESS model is integrated in the proposed schemes to enable the formulation of convex optimization problems that can be efficiently solved.

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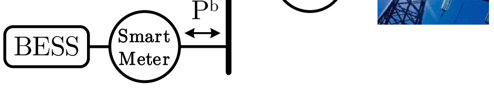

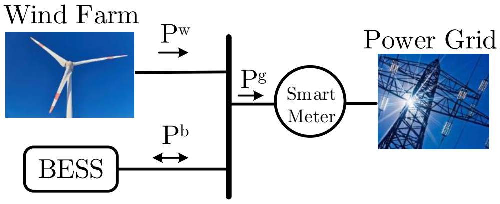

Fig. 1. The WPP with an integrated BESS.

The performance of the proposed schemes is evaluated and compared with the corresponding deterministic optimization scheme, using actual and forecasted power production data from a real-world WPP. In summary, the main contributions of this work are the following:

- Development of scenario-based stochastic and robust optimization schemes for the energy scheduling of wind-storage systems, proposing a methodology to appropriately select the scenario set based on the forecasted wind power production.
- Formulation of the proposed optimization schemes as linear programs that can be efficiently solved, without the requirement of using sophisticated optimization tools.
- Investigation of the trade-off between producer profits and power imbalances over the two schemes.

The rest of this paper is organized as follows. Sections II-IV formulate the deterministic, stochastic and robust optimization schemes as linear programs, respectively. The scenario selection methodology is explained in Section V and simulation results are presented in Section VI. Finally, conclusions are given in Section VII.

II. Deterministic Optimization Scheme

A BESS is considered and integrated in the WPP, as shown in Fig. 1. The deterministic optimization scheme assumes that the day-ahead prediction of the wind power generation is perfect and hence ignores power imbalances that occur from wind power uncertainty.

A. Objective Function

The objective function of the deterministic scheme is to maximize the system revenue by selling energy to the power grid based on the electricity prices, given by

$$\text{maximize} \quad F(\mathbf{P}^g) = \Delta T \sum_{t\in\mathcal{T}} c_t^g P_t^g, \tag{1}$$

where $\mathcal{T} = \{1, ..., T\}$ denotes the considered time horizon and ΔT the time-step duration in hours. Variable $P_t^g \geq 0$ denotes the power injected to the grid in MW at time-step t and parameters c_t^g denote the corresponding energy prices in €/MWh. $\mathbf{P}^g$ is a vector-form of variables P_t^g, $\forall t \in \mathcal{T}$.

B. Constraints

1) Power Balance: According to Fig. 1, the power balance between the wind power generation, BESS and power grid is defined as

$$P_t^w + P_t^b = P_t^g, \quad \forall t \in \mathcal{T}, \tag{2}$$

where variables P_t^w and P_t^b denote the produced wind power and the BESS charging (negative) or discharging (positive) power at time-step t in MW.

2) Wind Power: The upper bound of the produced wind power is defined by the forecasted wind power generation, $\overline{P}_t^w$, as

$$0 \leq P_t^w \leq \overline{P}_t^w, \quad \forall t \in \mathcal{T}. \tag{3}$$

Wind power curtailments are applied when $\overline{P}_t^w - P_t^w > 0$, which occurs when $c_t^g \leq 0$ in objective (1).

3) BESS Model: To model the BESS we consider the relaxed but convex model that we proposed in [11]

$$C_{t+1} = C_t + \Delta T(-P_t^b - P_t^L), \qquad \forall t \in \mathcal{T}, \tag{4a}$$
$$C_0 = I, \quad \underline{C} \leq C_t \leq \overline{C}, \qquad \forall t \in \mathcal{T}, \tag{4b}$$
$$-\overline{P}^c \leq P_t^b \leq \overline{P}^d, \qquad \forall t \in \mathcal{T}, \tag{4c}$$
$$P_t^L \geq e^d P_t^b, \quad P_t^L \geq (-e^c) P_t^b, \qquad \forall t \in \mathcal{T}, \tag{4d}$$
$$P_t^L \leq e^c \overline{P}^c + \alpha(P_t^b + \overline{P}^c), \qquad \forall t \in \mathcal{T}, \tag{4e}$$

where variables C_t and P_t^L denote the BESS state-of-charge (SoC) and the BESS power losses, respectively. Constants $\overline{P}^d$ and $\overline{P}^c$ denote the discharging and charging power limits, $\underline{C}$ and $\overline{C}$ the minimum and maximum SoC limits, and I the initial SoC. Moreover, constants $e^d = 1/\eta^d - 1$ and $e^c = 1 - \eta^c$ denote the positive discharging and charging losses coefficients, where η^d and η^c denote the one-way efficiency coefficients, and $\alpha = (e^d\overline{P}^d - e^c\overline{P}^c)/(\overline{P}^d + \overline{P}^c)$. The model is exact when the equality is attained in one of the two constraints in (4d), generating the optimal solution; otherwise, increased power losses are presented that may compromise the solution quality. More information regarding this model can be found in [11].

III. Stochastic Optimization Scheme

This section builds on the formulation of the deterministic optimization scheme to develop a two-stage stochastic optimization scheme that considers wind generation uncertainty; thus, the power imbalances between day-ahead and real-time markets are taken into account. Specifically, the proposed stochastic optimization scheme makes decisions in the day-ahead market (first stage), considering possible scenarios of the real-time market (second stage) [3].

A. Objective Function

The objective of the stochastic optimization scheme is to maximize the day-ahead market revenue $F(\mathbf{P}^g)$ and minimize the expected cost of the real-time market for a number of scenarios $\mathbb{E}[\hat{F}(\hat{\mathbf{P}}^g, \hat{\mathbf{P}}^v)]$ yielding the objective.

$$\text{minimize} \quad -F(\mathbf{P}^g) + \mathbb{E}[\hat{F}(\hat{\mathbf{P}}^g, \hat{\mathbf{P}}^v)]. \tag{5}$$

The expected cost of the second stage is given by

$$\mathbb{E}[\hat{F}(\hat{\mathbf{P}}^g, \hat{\mathbf{P}}^v)] = \Delta T \sum_{s\in\mathcal{S}} \phi_s (\sum_{t\in\mathcal{T}} (-c_t^g \hat{P}_{t,s}^g + M_t \hat{P}_{t,s}^v)), \tag{6}$$

where ϕ_s is the weighting parameter of scenario s such that $\sum_{s\in\mathcal{S}} \phi_s = 1$, and $\mathcal{S} = \{1, ..., S\}$ is the set of scenarios with $S = |\mathcal{S}|$; each scenario concerns the wind power production curve of the plant for one day. $\mathbf{P}^g$ is the vector-form of the first stage decision variables P_t^g, $\forall t \in \mathcal{T}$ indicating the scheduled grid power submitted to the day-ahead market. $\hat{\mathbf{P}}^g$,

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$\hat{\mathbf{P}}^v$ are vector-forms of the second stage (real-time market) decision variables $\hat{P}^g_{t,s}$, $\hat{P}^v_{t,s} \geq 0$, $\forall t \in \mathcal{T}, s \in \mathcal{S}$ indicating the grid power adjustments in the *allowed imbalance band* and grid power violations[1] in MW at time-step t of scenario s, respectively. Constant M_t denotes the penalty cost in €/MWh associated with the violated energy due to grid power violations at time-step t. In this work, we assume that the electricity prices, c^g_t, are known and remain unchanged over the trading hours of the day-ahead and real-time markets.

B. First-Stage Constraints

The constraints of the first stage are set as

$$\text{Constraints:} \quad (2), (4a)\text{-}(4e), \tag{7a}$$

$$0 \leq P^w_t \leq \overline{P}^c, \quad \forall t \in \mathcal{T}, \tag{7b}$$

where the produced wind power in (7b) is limited by the wind power capacity $\overline{P}^c$. In the stochastic optimization scheme the produced power P^w_t, $\forall t \in \mathcal{T}$ is first-stage variable defined by the wind power production profiles of the selected scenarios.

C. Second-Stage Constraints

1) Power Balance: Wind power deviations between the actual $P^{w,a}_{t,s}$ and scheduled power generation P^w_t need to be compensated to ensure power balance. When $P^{w,a}_{t,s} - P^w_t \geq 0$ the excess power can be exploited by increasing the injected power into the grid by $\hat{P}^g_{t,s} \geq 0$ or storing power equal to $\hat{P}^b_{t,s} \leq 0$ in the BESS, provided that associated constraints are satisfied; any remaining excess power $\hat{P}^c_{t,s} \geq 0$ is curtailed. When $P^{w,a}_{t,s} - P^w_t \leq 0$ the power deficiency can be compensated by reducing the injected power into the grid by $\hat{P}^g_{t,s} \leq 0$ or releasing power equal to $\hat{P}^b_{t,s} \geq 0$ from the BESS, provided that associated constraints are satisfied; any remaining power deficiency $\hat{P}^v_{t,s} \geq 0$ is penalized. These conditions yield

$$\hat{P}^b_{t,s} + (P^{w,a}_{t,s} - P^w_t) - \hat{P}^c_{t,s} + \hat{P}^v_{t,s} = \hat{P}^g_{t,s}, \ \forall t \in \mathcal{T}, \forall s \in \mathcal{S}. \tag{8}$$

2) Grid Power Adjustments: The grid power adjustments in the *allowed imbalance band* are confined to a percentage ρ of the scheduled grid power such that

$$-\rho P^g_t \leq \hat{P}^g_{t,s} \leq \rho P^g_t, \quad \forall t \in \mathcal{T}, \forall s \in \mathcal{S}. \tag{9}$$

3) Power Curtailments: The bounds of the wind power curtailments are defined by the actual wind generation of each scenario, given by

$$0 \leq \hat{P}^c_{t,s} \leq P^{w,a}_{t,s}, \quad \forall t \in \mathcal{T}, \forall s \in \mathcal{S}. \tag{10}$$

4) ESS Power and Energy Adjustments: The equations describing the adjustment of the charging/discharging power and SoC of the BESS during real-time operation (second-stage) are given by

$$\hat{C}_{t+1,s} = \hat{C}_{t,s} + \Delta T(-P^b_t - \hat{P}^b_{t,s} - \hat{P}^L_{t,s}), \ \forall t \in \mathcal{T}, \forall s \in \mathcal{S}, \tag{11a}$$

$$\hat{C}_{0,s} = I, \quad \underline{C} \leq \hat{C}_{t,s} \leq \overline{C}, \qquad \forall t \in \mathcal{T}, \forall s \in \mathcal{S}, \tag{11b}$$

$$-\overline{P}^c \leq P^b_t + \hat{P}^b_{t,s} \leq \overline{P}^d, \qquad \forall t \in \mathcal{T}, \forall s \in \mathcal{S}, \tag{11c}$$

$$\hat{P}^L_{t,s} \geq e^d(P^b_t + \hat{P}^b_{t,s}), \qquad \forall t \in \mathcal{T}, \forall s \in \mathcal{S}, \tag{11d}$$

$$\hat{P}^L_{t,s} \geq (-e^c)(P^b_t + \hat{P}^b_{t,s}), \qquad \forall t \in \mathcal{T}, \forall s \in \mathcal{S}, \tag{11e}$$

$$\hat{P}^L_{t,s} \leq e^c\overline{P}^c + \alpha(P^b_t + \hat{P}^b_{t,s} + \overline{P}^c), \quad \forall t \in \mathcal{T}, \forall s \in \mathcal{S}, \tag{11f}$$

where $\hat{C}_{t,s}$ and $\hat{P}^L_{t,s}$ denote the BESS SoC and BESS power losses of scenario s at time t, respectively.

[1]The term *grid power violations* is defined as the amount of power that is outside the *allowed imbalance band* around the scheduled grid power.

IV. Robust Optimization Scheme

The robust optimization scheme also handles the wind power uncertainty by making decisions in the day-ahead market, considering possible scenarios of the real-time market. Specifically, this scheme generates a solution that optimizes the worst-case scenario.

A. Objective Function

The objective of the robust scheme is to maximize the day-ahead market revenue $F(\mathbf{P}^g)$ and minimize the real-time market cost of the worst-case scenario β, yielding

$$\text{minimize} \quad -F(\mathbf{P}^g) + \beta. \tag{12}$$

B. Constraints

1) First/Second Stage Constraints: The constraints associated with the day-ahead and real-time markets are the same with the ones of the stochastic optimization scheme, i.e., constraints (7a)-(11f).

2) Worst-Case Scenario Cost: The cost of the worst case scenario β is defined by

$$\Delta T \sum_{t \in \mathcal{T}} (-c^g_t \hat{P}^g_{t,s} + M\hat{P}^v_{t,s}) \leq \beta, \quad \forall s \in \mathcal{S}. \tag{13}$$

The left-hand side term represents the cost/revenue of scenario s in the real-time market. Minimizing variable β in (12) ensures that β attains the cost of the most costly scenario.

V. Scenario selection

For the stochastic and robust schemes we select a subset of the historical actual wind power generation curves which are closest to the day-ahead forecasted curve. Towards this direction, we utilize the Euclidean distance with the forecasted curve, given by [12]

$$d_k(\mathbf{W}, \mathbf{A}_k) = \sqrt{\sum_{t \in \mathcal{T}} (W_t - A_{t,k})^2}, \quad k \in \mathcal{K}, \tag{14}$$

where $\mathbf{W}$ is the time series vector of the forecasted curve, $\mathbf{A}_k$, $\forall k \in \mathcal{K}$ is the time series vector of the kth historical actual power generation curves, and $\mathcal{K}$ is the corresponding set. Then, the set of scenarios $\mathcal{S}$ is formed by the θ curves with the smallest Euclidean distance and the forecasted curve.

The scenario weights in the stochastic scheme are defined based on an importance factor $f_s \in [0, 1]$, $\forall s \in \mathcal{S}$ that aims to put more importance on scenarios with small Euclidean distance. Factor f_s is defined as

$$f_s = 1 - \frac{d_s(\mathbf{W}, \mathbf{A}_s)}{d^{max}}, s \in \mathcal{S}, \tag{15}$$

where $d^{max} = \max_{k \in \mathcal{K}}\{d_k(\mathbf{W}, \mathbf{A}_k)\}$. Note that the importance factor of the prediction curve $\mathbf{W}$ is equal to one

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because the corresponding Euclidean distance is equal to zero. Normalizing the importance factors yields the scenarios weights ϕ_s defined as

$$\phi_s = f_s / \sum_{s \in \mathcal{S}} f_s. \tag{16}$$

VI. Simulation Results

This section investigates the performance of the three optimization schemes using real data from a 10.8 MW ($\overline{P}^c = 10.8$ MW) WPP located in Larnaca, Cyprus. We consider an integrated BESS with usable capacity of 2 MWh ($\underline{C} = 0$, $\overline{C} = 2$ MWh), charging/discharging power of 4 MW ($\overline{P}^c = \overline{P}^d = 4$ MW) and one-way efficiency of 96% ($\eta^d = \eta^c = 0.96$). The day-ahead energy prices c_t^g, depicted in Fig. 2, are assumed to be known. The grid power adjustments and the penalty cost for the grid power violations are set to $\rho = 10\%$ and $M_t = 80$ €/MWh, $\forall t \in \mathcal{T}$, respectively.

All problems are coded in Matlab and solved using optimization solver Gurobi [13] on a personal computer with 8 GB RAM and an Intel Core-i5 3.2 GHz processor. The horizon is set to one day with 30-minute time intervals.

The optimization schemes are evaluated over the period 01/06/2021-31/08/2021 using real WPP data. Specifically, the forecasted wind power generation curves of the evaluation period as well as actual wind power generation curves from the years 2019 and 2020 are used in the optimization schemes, selecting the scenario curves according to Section V. To evaluate the performance of the schemes, the actual power generation curves of the evaluation period are utilized to calculate the daily WPP profits and the penalized energy due to power imbalances. Unless otherwise stated, we set $\theta = 30$ so that a total of $S = 31$ scenarios are selected for each problem. Next, Section VI-A investigates the performance of the optimization schemes for a single day, Section VI-B presents aggregate results for the whole period, and Section VI-C examines the execution speed of the schemes.

A. Performance evaluation

The performance of the three optimization schemes is studied for the evaluation day 31/07/2021. Fig. 3 illustrates the forecasted and actual power generation curves of the considered day, as well as the selected scenario curves according to Section V. The scheduled grid power using the three optimization schemes without the BESS ($\overline{P}^c = \overline{P}^d = 0$ MW) is demonstrated in Fig. 4(a)-(c). As expected, the scheduled grid power of the deterministic scheme follows the forecasted curve, while this is not true for the stochastic and robust schemes that consider multiple scenarios. Specifically, the robust scheme generates the most conservative solution by avoiding the scheduling of high amounts of power to be injected into the grid that may cause high penalty costs. The actual WPP profits and the penalized energy using the three schemes without and with the BESS are shown in Table I. As expected, the usage of the BESS increases the profits and reduces the penalized energy in all schemes. Interestingly, the stochastic scheme achieves an increment of 8.5% (287€) and a reduction of 31.61% (7.99 MWh) on the profit and

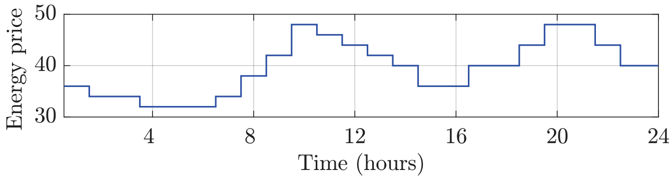

Fig. 2. Variable electricity pricing scheme (€/MWh).

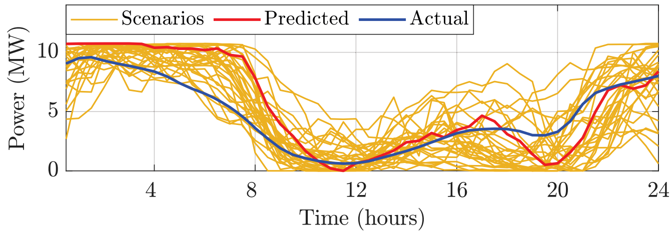

Fig. 3. Wind power production curves: The forecasted and actual power generation for 31/07/2021, as well as 30 selected scenario curves obtained from historical data from the years 2019 and 2020.

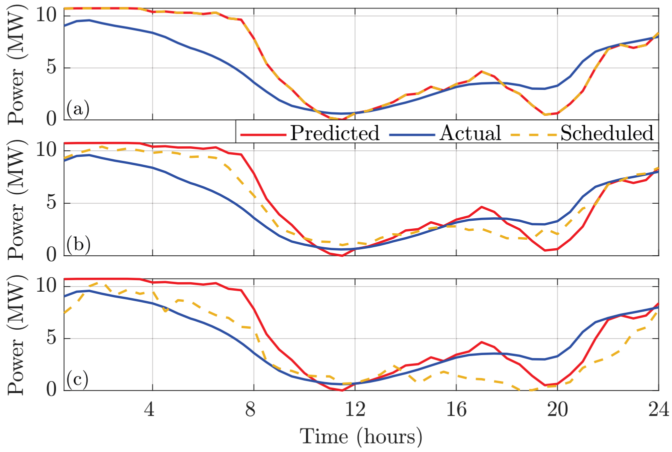

Fig. 4. Scheduled grid power without the BESS using the (a) deterministic, (b) stochastic, and (c) robust optimization scheme.

TABLE I
PERFORMANCE EVALUATION OF THE THREE OPTIMIZATION SCHEMES

Performance metric	**Deterministic**	**Stochastic**	**Robust**
Actual profits without BESS	3,110 €	3,606 €	3,089 €
Actual profits with BESS	3,373 €	3,660 €	3,153 €
Penalized energy without BESS	27.98 MWh	18.36 MWh	9.84 MWh
Penalized energy with BESS	25.27 MWh	17.28 MWh	9.44 MWh

penalized energy, respectively, compared to the deterministic scheme when the BESS is used. Similarly, the robust scheme achieves a high reduction of 58.68% (14.83 MWh) on the penalized energy, but also reduces the profits by 6.5%. Note that the presented results with the BESS account for an extra performance loss due to the use of the relaxed BESS model. Non-exactness occurs when wind power curtailments are applied in the stochastic and robust schemes. In such cases, extra BESS energy losses are introduced as an alternative power curtailment form by violating the BESS relaxation exactness, without affecting the solution feasibility.

B. Aggregate performance evaluation

The aggregate performance of the three optimization schemes with and without the BESS is investigated for the evaluation period 01/06/2021-31/08/2021. Fig. 5(a) illustrates

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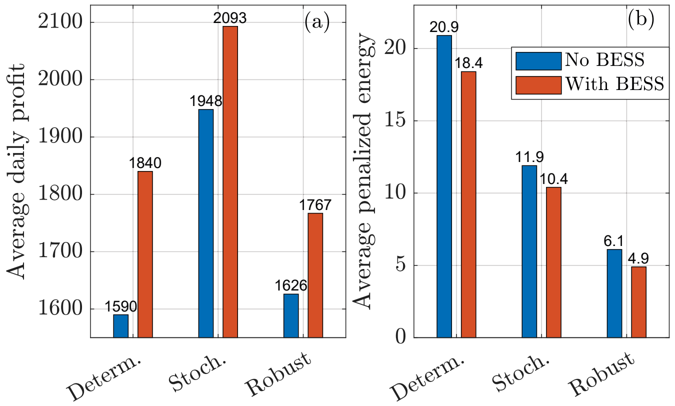

Fig. 5. Aggregate daily results for the evaluation period using the deterministic, stochastic, and robust optimization schemes with and without BESS: (a) Average daily profits (€) and (b) average penalized energy (MWh).

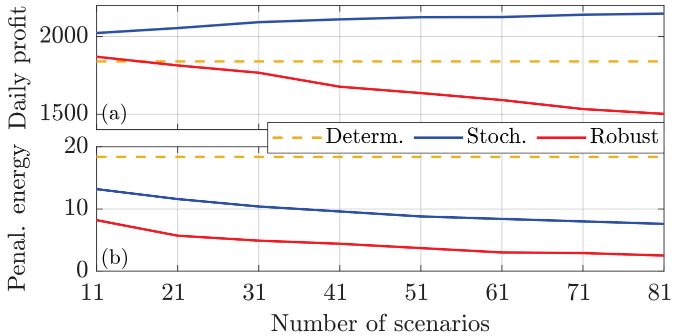

Fig. 6. Aggregate daily results using the stochastic and robust optimization schemes with BESS, under a different number of scenarios: (a) Average daily profits (€) and (b) average penalized energy (MWh).

TABLE II
EXECUTION SPEED FOR DIFFERENT NUMBER OF SCENARIOS

Optimization scheme	$S = 31$	$S = 51$	$S = 101$	$S = 201$
Stochastic	0.29 s	0.48 s	1.00 s	3.14 s
Robust	0.44 s	0.51 s	1.01 s	2.66 s

an increment on the average daily profits of the deterministic, stochastic and robust schemes by 15.72% (250€), 7.45% (145€) and 8.67% (141€), respectively, when the BESS is utilized. Interestingly, the stochastic scheme achieves the maximum profits of 1948€ and 2093€ without and with BESS, while the robust and deterministic schemes generate similar profits. Fig. 5(b) depicts a reduction on the average penalized energy of the deterministic, stochastic and robust schemes by 11.96% (2.5 MWh), 12.6% (1.5 MWh) and 19.67% (1.2 MWh) when the BESS is used. As expected, the robust scheme achieves the lowest penalized energy of 4.9 MWh followed by the stochastic and deterministic schemes with 10.4 MWh and 18.4 MWh, respectively, using the BESS.

Fig. 6 illustrates the (a) average daily profits and (b) average penalized energy resulting from the stochastic and robust schemes with BESS for varying number of scenarios. It is observed that the stochastic scheme increases the profit and reduces the penalized energy as the considered number of scenarios increases, always achieving a significant better performance compared to the deterministic scheme. As expected, the robust scheme also reduces the penalized energy with the increment of the scenarios, achieving the lowest value of 2.5 MWh for $S = 81$; however, the daily profits are also reduced because this scheme becomes more conservative as the scenarios increase.

C. Execution speed

This section investigates the execution speed of the stochastic and robust optimization schemes with BESS for the evaluation day 31/07/2021. Table II shows the small execution times of the two schemes under an increasing number of scenarios, indicating that the formulated linear programs can be solved efficiently even under a large number of scenarios. Note that in this work we use a commercial optimization tool [13], but this is not necessary.

VII. Conclusions

This work develops two-stage scenario-based stochastic and robust optimization schemes for the day-ahead energy scheduling of wind-storage systems. The two schemes as well as the corresponding deterministic scheme are formulated as linear programs that can be solved efficiently. Two main remarks can be drawn from the results. First, the stochastic and robust schemes are preferable compared to the deterministic scheme, achieving higher profits and lower power imbalances. Second, the two schemes offer a different trade-off between profits and power imbalances, making the stochastic scheme more desirable to the WPP due to higher profits and the robust scheme to the system operator due to lower power imbalances. Future work will consider electricity price uncertainty.

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