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Dust effect impact on PV in an aggregation with wind and thermal powers

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ABSTRACT

This paper is about the dust effect impact on photovoltaic systems on the profit of an electricity market agent acting as an aggregator of photovoltaic power, wind power, thermal power, and an energy storage system. Energy storage ensures arbitrage and smoothing of the variability of photovoltaic power and wind power. The market agent intends to derive bids for submission in a day-ahead market, having consideration of the dust effect impact on the photovoltaic power. A formulation is proposed for a support decision system by a profit-based unit commitment problem solved by a stochastic programming approach, considering the operating characteristics of the virtual power plant. The photovoltaic power, wind power, and market price uncertainties are input data derived from scenarios of historical data. Case studies addressed show the advantages of the stochastic programming approach and insights concerned with the integration of uncertainties within the modeling for the schedule of the energy storage system and the dust effect impact on profit.

1. Introduction

The integration of photovoltaic (PV) power in the mix of production of an electricity market is a trending of a research topic over the past decade. But nowadays, several issues not relevant at levels of lower integration of PV power are raising at large integration ones [1]. Therefore, convenient anticipated assessment of the PV system output can play a role in the decision-making through an improved interface with the unit commitment and the economic dispatch. Moreover, this assessment can allow a more profitable and reliable operation by mitigating the impact of uncertainty, augmented due to the integration in the electricity market. This assessment must take into account the effects that influence the performance of the PV system. For instance, environment conditions [2], namely, temperature, wind speed, solar radiance or radiation [3], device aging, damage, shading, deposition of dust due to human activities or natural dust accumulation, influence performance.

The deposition of dust on PV systems attenuates the capture of the radiation reaching the PV cells by reducing the overall transmissivity at the level of the glass cover and hence is responsible for a decrease in the PV system performance [4–6]. Besides this attenuation, if the deposition of dust is not even equal over the PV cells, hot points appear, which over a due time can burn the cells, i.e., permanently damaged in the cells is expected in due time [7,8]. Wind speed and rain can help in the cleaning of dust, but also installation tilt, azimuth angles, and the location where the PV system is at the outdoor exposing conditions affect dust accumulation density on surfaces [9]. Hence, the reduction in PV system performance due to the deposition of dust is highly dependent on the in-situ conditions [5].

Studies on the impact of deposition of dust on PV systems addressed in what regards the analysis of the reduction in PV power output are conclusive about the importance of this impact, for instance: Ref. [10] reports a 26% reduction for concentrated PV systems in Spain; Ref. [11] reports around 4.4% annual average reduction and in a long time without rain exceeding a daily 20% reduction for a tested small PV system on a roof in Spain; Ref. [12] reports a 6.9% reduction as a result of deposition of sandy soil on a PV system in Italy; Ref. [13] reports around 4% in a laboratory study of a PV system in Germany; Ref. [14] reports a 13.7% to 16.5% reduction in Minas Gerais, Brazil; Ref. [15] reports a 4.5% reduction in Australia. There are regions where the reported reduction is even more significant, for instance: Ref. [16] reports a 35% to 40% reduction in Northern Oman; Ref. [17] reports a

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Nomenclature

Abbreviations

DAM	Day-ahead market
ESS	Energy storage system
MIBEL	Iberian Electricity Market
MILP	Mixed integer linear programming
PSO	Particle swarm optimization
PV	Photovoltaic
WP	Wind Power

Sets and indexes

I, i	Set and index of thermal units
L, l	Set and index of segments for piecewise linear cost function of thermal units
S, s	Set and index of scenarios
T, t	Set and index of periods in the time horizon

Parameters and Constants

α	Dust effect parameter
λ_{st}^{D}	DAM clearing price for scenario s at period t
λ_{st}^{+}	Positive imbalance price for scenario s at period t
λ_{st}^{-}	Negative imbalance price for scenario s at period t
η^{ChESS}	ESS charging efficiency
η^{DiESS}	ESS discharging efficiency
PR_t^{+}	Ratio between positive imbalance price and DAM price at period t
PR_t^{-}	Ratio between negative imbalance price and DAM price at period t
A_i	Thermal unit i fixed cost
F_i^{l}	Thermal unit i slope of segment l of the piecewise linear variable cost function
J_i	Thermal unit i imposed number of periods offline
K_i^{β}	Cost of the βth interval of the start-up cost of thermal unit i
N_i	Thermal unit i imposed number of periods online
$P_{st}^{ChESS\max}$	Maximum charging power of the ESS for scenario s at period t
$P_{st}^{DiESS\max}$	Maximum discharging power of the ESS for scenario s at period t
P_i^{min}, P_i^{max}	Thermal unit i ramp-up and ramp-down
P_{st}^{PV}	PV power for scenario s at period t
$P^{PV\max}$	Maximum PV power system power capacity
P_{st}^{W}	WP for scenario s at period t
$P^{W\max}$	Maximum wind system power capacity
RU_i/RD_i	Thermal unit i ramp-up/ramp-down
SDC_i	Thermal unit i shut-down cost
SU_i/SD_i	Thermal unit i start-up and shut-down ramp rate
s_{si0}	Thermal unit i offline time at the beginning of the time horizon for scenario s
T_i^{l}	Thermal unit i segment l upper limit of the piecewise linear variable cost function
UT_i/DT_i	Thermal unit i minimum up/down time

Continuous variables

δ_{sit}^{l}	Segment power l of thermal unit i for scenario $s$at period t
d_{st}	Imbalance for scenario s at period t
d_{st}^{+}	Positive energy deviation for scenario s at period t
d_{st}^{-}	Negative energy deviation for scenario s at period t
e_{st}^{ESS}	ESS energy for scenario s at period t
p_{sit}	Thermal unit i power generated for scenario s at period t
p_{sit}^{max}	Thermal unit i maximum available power for scenario s at period t
b_{sit}	Thermal unit i linearized variable cost function for scenario s at period t
p_{st}^{ChESS}	ESS charging power for scenario s at period t
p_{st}^{DiESS}	ESS discharging power for scenario s at period t
p_{st}^{Total}	Total energy bid to be submitted to the DAM for scenario s at period t
SUC_{sit}	Thermal unit i start-up cost of ESS for scenario s at period t

Binary (0/1) variables

k_{st}^{Ch} /	k_{st}^{Di} ESS decisions for scenario s at period t: 1, if charges/discharges; 0, otherwise
t_{sit}^{l}	Thermal unit i decision for scenario s at period t: 1, if the power exceeds the power of segment l; 0, otherwise
u_{sit}	Thermal unit i commitment decision for scenario s at period t
y_{sit}	Thermal unit i start-up decision for scenario s at period t
z_{sit}	Thermal unit i shut-down decision for scenario s at period t

32% reduction in Lebanon; Ref. [18] reports a 22% reduction for a 70-day experiment in Iran; Ref. [19] reports a 43% reachable reduction in a PV system at the Cyprus University of Technology, due to clouds of dust moving from the Sahara Desert to Cyprus.

1.1. Unit commitment

The unit commitment problem is a decision problem concerned with the scheduling of units at each period over a time horizon and admits a processing structure divided into two sub-problems: (i) the sub-problem determining the units on/off status at each period of the time horizon; (ii) the sub-problem of the economic dispatch determining the power output of units in each period of the time horizon [20]. Unit commitment is the most relevant task for power systems management [21], either in the view of the past paradigm for regulated markets or of the nowadays for deregulated markets. The past unit commitment, i.e., in the view of the paradigm for regulated markets, is a minimization of cost while meeting the load demand and the operational constraints of the power system. While in the view of the nowadays paradigm, the unit commitment is a maximization of profit subjected only to the operational constraints. Under nowadays paradigm, market players have an environment for business settling new opportunities. But market players must have a support decision system to exploit the opportunities advantageously. Hence, a power producer must have a price-based unit commitment as a support decision system to exploit the opportunities conveniently [22]. The state-of-art about the approaches for the unit commitment problem shows lines of research using heuristics, conventional optimization, stochastic optimization, artificial intelligence, or even hybrid approaches.

Approaches proposed for the unit commitment problem involves, for instance: priority list [23], dynamic programming [24], Lagrangian relaxation [25], mixed-integer programming [26–28]. Priority list approaches are easily implemented and have little processing time, but these approaches do not ensure that the solution is in an acceptable neighborhood of the optimal solution [29]. Dynamic programming is the earliest optimization approach applied to unit commitment problems but suffers from the narrowness known as the curse of dimensionality. Mixed-integer linear programming (MILP) proved to be a successful approach in what regards the flexibility and extensive modeling capability offered [26,27]. Most of the conventional approaches have limitations on the ability to provide the optimum for the non-differentiable and discontinuous formulation of unit commitments. Hence, the state-of-art shows a line of research with approaches developed using metaheuristics, genetic or evolutionary optimization approaches, namely artificial neural networks, particle swarm optimization (PSO) [30–32]. These approaches have a wide recognition due to easy implementation, allowing more complex formulations and being able to achieve solutions in a near neighborhood of the optimal solutions. Also, these approaches appear as a part of procedures in what are the so-called hybrid approaches, trying for profiting simultaneously from advantages the conventional ones, particularly convex optimization, and metaheuristics, genetic, or evolutionary approaches. Hybrid approaches for more complex formulations of constraints in unit commitment problems can carry out the optimization with advantageous appropriated performance. For instance: Ref. [33] presents a hybridization of Lagrangian relaxation with genetic algorithm; Ref. [34] presents a hybridization of Lagrangian relaxation with PSO; Ref. [35] presents a hybridization of dynamic programming with PSO; Ref. [36] presents a priority list with a hybrid genetic-imperialist competitive algorithm. Another line of research uses stochastic optimization regarded as relevant to handle bidding strategy of aggregation of energy resources with uncertainty on the availability of renewable energy sources. These resources must be conveniently modeled so that the power producer decision-making under uncertainty is further tuned in what regards the achievement of convenient operation [37,38]. The electricity market is nowadays in the way of following in the smart grid context experiences that are significant changes with the way of doing things [39–42], known to be the business as usual. The electricity market is opening to the participation of new market players, namely aggregators of energy resources and small-scale renewable energy producers [43].

The use of stochastic optimization in unit commitment problems is a line of research tackled in the way of the future, for instance: Ref. [44] presents a stochastic optimization for solving a unit commitment problem with uncertainty model by particle swarm optimization to select optimal scenarios; Refs. [45,46] presents a comparison between stochastic optimization with deterministic optimization allowing to conclude that the former is more convenient. Under nowadays paradigm, the unit commitment problem formulation must consider uncertainty to account not only for the availability of renewable energy sources but also for the possible scenarios of market prices. Hence, stochastic optimization is, without doubt, a line of research in the way of the future. Stochastic optimization employs decomposition techniques consisting of Progressive Hedging [47], Lagrangian relaxation [48], Dantzig–Wolfe Decomposition [49], or Benders Decomposition [50]. These techniques appear in the formalizations of two or multi-stage approaches, decomposing problems by stages, scenarios, or by generation units. Other lines of research are in the scope of the application of Game Theory approaches concerned with the simulation of the market power for market agents in the unit commitment. A report summarizing the application of optimization techniques for solving unit commitment problems addressing a formalization in what regards the aggregation of power units is in Table 1.

As the penetration of renewable energy increases and became enough perceptible in the mix of generation, i.e., became a large penetration of renewable energy, the demands for flexible options increase [56]. An energy storage system (ESS) can play among the flexible options a meaningful role [57]. An ESS is significant not only for improving the overall stability and reliability of the power system [38,58] but also for arbitrage and smoothing on the variability of PV and wind power (WP) exploitation. Ref. [59] presents a review of ESSs for usage jointly with renewable energy. Ref. [23] presents an approach for a thermal unit commitment coordinated with an ESS, having thermal scheduling implemented by an extended priority list. Ref. [51] presents optimal scheduling solved by a PSO algorithm for a thermal unit commitment coordinated with WP and an ESS by a pumped hydro. Ref. [52] presents a stochastic unit commitment problem having as ESS a battery and using sub-hourly intervals in the second stage of the optimization, i.e., in the real-time market. Ref. [53] presents a stochastic unit commitment having WP coordinated with an ESS, smoothing the variability of power. Also, a classification of ESS and criteria for the selection of a specific ESS are presented. Ref. [54] presents a stochastic unit commitment problem adapted for optimal coordination of thermal units, renewable energy, and electric vehicles. Ref. [55] presents a stochastic unit commitment for thermal units and combined cycle gas turbines, taking into consideration constraints due to emissions.

1.2. Research quiz and contributions

Integration of renewable energy can represent a challenge for power systems, requiring a convenient approach for scheduling energy conversion into electric energy under the nowadays paradigm. Unlike the behavior of conventional power plants, the behavior of renewable power plants requires the consideration of stochasticity. Besides, the deposition of dust in PV modules can deliver added stochasticity in the behavior of renewable energy. As a result of the ongoing work by the authors, this paper reports significant improvement in the work previously published in Refs. [37,38]. The main contributions of this work are as follows:

- C1 — A support management system based in two-stage linear stochastic programming to explore the advantages of aggregation of distinct power sources including renewable energy for the participation of an aggregator in electricity markets;
- C2 — An arbitrage for ESS in the support management system of the aggregator, i.e., considering a model for arbitrage jointly within the formulation of the support management system based in two-stage linear stochastic programming;

Table 1
Unit commitment formulations addressing aggregation.

Aggregation power	Method	Objective function	Reference
Thermal units, energy storage	Extended Priority list	Operating costs	[23]
Thermal units,WP, pump-storage plant	PSO	Operating costs	[51]
Thermal units, WP, energy storage device	Stochastic programming	Operating costs	[52]
Thermal units, WP, energy storage device	Stochastic programming	Operating costs	[53]
Thermal units, WP, electric vehicles	Stochastic programming	Operating costs	[54]
Thermal units, combined cycles units	Stochastic programming	Expected profit	[55]

- C3 — A formulation for the consideration of the dust accumulation, i.e., an impact of dust accumulation on PV modules in the PV power output, and consequently the impact in the expected profit of the aggregator.

A comparison between the references used in Table 1, regarding some unit commitment formulations addressing aggregation, and this paper is in Table 2.

The trend of management of a mix of power sources by a single entity, the aggregator, is pivotal knowledge in the scope of the future electricity markets, smart grids, and smart cities. Since as expected in the future, the power system is a blend of small microgrids managed by aggregators, having the capability of importing or exporting electric energy. Mostly, this paper is about a profit-based stochastic unit commitment concerned with the aggregation of renewable energy, namely WP and PV powers, with thermal unit power, and ESS. This profit-based stochastic unit commitment is a contribution in adding an efficient aggregation of renewables with thermal units and ESS, giving better decisions in what regards the stochasticity to be faced.

Research on the capability of ESS to smooth the integration of WP and PV power take place widely reported. Nevertheless, there is a line of research on the capability of ESS to produce arbitrage about the impact of the scenarios of market prices and the power output of renewables that needs further appraisal. This paper contributes to this line of research considering arbitrage due to ESS to provide possible compensation for energy deviations. Consequently, the incomes to the aggregator are a function of the scenarios of market prices and the power output of renewables. Also, research on the dust accumulation on PV modules takes place widely reported at the technical level and less reported in what refers to the economic implications. Nevertheless, an analysis of the impact of dust accumulation on PV modules lacks in what regards the viewpoint of the bidding assessment of a market agent. Also, this paper contributes to this line of research.

2. Electricity market

The day-ahead market (DAM) is the platform where, after the clearing of the market, the electric energy is through the next-day operation of the grid conveyed from the power producers for physical delivery to consumers. The structure of a deregulated electricity market is in Fig. 1.

In Fig. 1 the market operator is the entity responsible for setting the price at each period of the next day in the DAM. This setting of the price is a crossing of offers of selling with purchase ones coming from agents registered in the market. The offer must indicate the period, the price, and the corresponding amount of energy traded in the respective period. These offers are in curves known as the supply curve or the demand curve, respectively, in increasing order or decreasing order of the prices. The crossing process is the process of the intersection of supply and demand curves at each period, defining the price of the energy traded in the period. Hence, this price ensures that at the clearing of the market, the accepted supply meets the accepted demand at each period, and the price is the lowest one. But the supply and demand accepted at the clearing are not necessarily in per with the ones needed at the time of delivery, i.e., in due time, imbalances happen due to failure to meet the accepted traded levels of energy. For instance: an aggregator managing renewable energy sources is most probably faced either with more energy or less energy than the one accepted at the clearing of the market due to the uncertainty on availability of WP, PV power, or the deposition of dust on the PV panels.

The system operator is the entity responsible for proceeding in the way of keeping the balance between production and usage of energy in due time to cope with the imbalance in a market environment called the balancing market. The system operator of the balancing market of the Iberian Electricity Market (MIBEL) subjects the market agents to a price for a positive energy imbalance and another for negative energy imbalance. The price for a positive energy imbalance is due to higher production or lower consumption than the one accepted at the clearing of the DAM. The price for negative energy imbalance is due to lower production or higher consumption than the one accepted at the clearing of the DAM [38]. The procedure for pricing imbalances [60,61] in MIBEL is in Table 3.

Table 3 shows that in case of a positive system imbalance, the producers with overproduction comparatively to the energy accepted at the market-clearing are paid by the excess energy at price λ_t^{DN}, typically this price is lower than the DAM clearing price λ_t^{D}. Consequently, the profit expected is lesser than the one given if the overproduction is in the offer of the previous day. While market participants subject to the price λ_t^{D} can produce less energy than that accepted at the market-clearing. This price for these participants is because the balance of the system is favorable to underproduction due to the overall excess production. In the case of a negative system imbalance, the producers with underproduction pay for the underproduction at a price, λ_t^{UP}, typically this price is higher than the price λ_t^{D}. Again, the profit expected is lesser than the one given if the underproduction is not in the offer of the previous day, i.e., the offer is the one feasible to be satisfied. While market participants subject to the price λ_t^{D} can produce more energy than that accepted at the market-clearing. This price for these participants is because the balance of the system is favorable to overproduction due to the overall less production.

3. Methodology

The two-stage stochastic optimization approach can deal with the uncertainties related to renewable energy exploitation and market prices, processing scenarios in an arrangement expressed by a scenario tree obtained by the utilization of the available historical data processed by a suitable scenario reduction tool. The two-stage stochastic optimization approach admits a reasonable formulation as a MILP approach, allowing to benefit from the available and well-proven practical commercial optimization solvers for MILP, and this paper proposes to use commercial optimization solvers for MILP for the practical solution of the approach. A summarization of the theoretical basis for the management of the aggregator under uncertainty, namely, the two-stage stochastic optimization approach, the ESS modeling, and the thermal unit modeling is in what follows.

Table 2
Comparison between this paper and references in Table 1.

Features of this paper	Reference					
	[23]	[51]	[52]	[53]	[54]	[55]
Thermal units	Yes	Yes	Yes	Yes	Yes	Yes
WP	No	Yes	Yes	Yes	Yes	Yes
PV power	No	No	No	No	No	No
ESS	Yes	No	Yes	Yes	No	No
Stochastic programming	No	No	Yes	Yes	Yes	Yes
Profit-based stochastic UC	No	No	No	No	No	Yes
ESS arbitrage as a function of the scenarios of electricity market prices	No	No	No	No	No	No
Dust effect	No	No	No	No	No	No

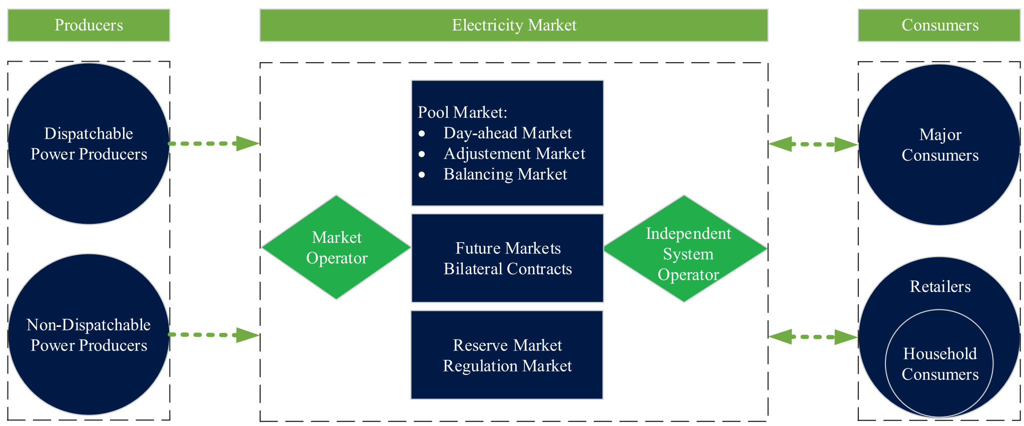

Fig. 1. Deregulated electricity market structure.

3.1. Two-stage stochastic programming approach

The formulation for the two-stage linear stochastic programming is [62] as follows:

$$\max c^T x + E\left[\max_{y_\omega} q_\omega^T y_\omega\right] \tag{1}$$

Subject to:

$$\underline{b} \le Ax \le \overline{b} \tag{2}$$

$$\underline{h_\omega} \le T_\omega x + W_\omega y_\omega \le \overline{h_\omega}, \forall\omega \tag{3}$$

$$x \ge 0, y_\omega \ge 0, \forall\omega \tag{4}$$

In (1) the second term is the expected second-stage value. In (3) T and W are, respectively, referred to as the technology and the recourse matrices, respectively. The two-stage stochastic programming formulated from (1) to (4) is expressed in a deterministic equivalent program as follows:

$$\max_{x,y_\omega} c^T x + \sum_{\omega}^{\Omega} \rho_\omega q_\omega^T y_\omega \tag{5}$$

Subject to:

$$\underline{b} \le Ax \le \overline{b} \tag{6}$$

$$\underline{h_\omega} \le T_\omega x + W_\omega y_\omega \le \overline{h_\omega}, \forall\omega \tag{7}$$

$$x \ge 0, y_\omega \ge 0, \forall\omega \tag{8}$$

In (5) the second term is the recourse function or expected second-stage value function. Ref. [62] presents more detail about stochastic programming. In the scope of this paper, the categorization of the decision variables are as follows:

- D1 — First stage decisions, given in the vector x, which are also known as here and now decisions, are made before the realization of uncertainties, which in the scope of the formulation in this paper are: WP, PV power and market prices for energy and market prices for imbalance, known as imbalance prices. The hourly bids are first-stage decisions. The objective is the maximization of the profit of the aggregation of production in the first stage;
- D2 — Second stage decisions, given in the vector y, which are known as wait and see decisions are made after the realization of the first-stage decisions. Second stage decisions are related to the commitment decisions of thermal units and economic dispatch over the time planning horizon, i.e., the power output of units in each period of the planning horizon and the charge/discharge status of the ESS. The objective of the optimization problem is the maximization of the expected profit in the second stage.

Table 3
Imbalance pricing.

		System imbalance	
		Negative	Positive
Power producer imbalance	Negative	$\lambda_t^- = \max(\lambda_t^D, \lambda_t^{UP})$	$\lambda_t^- = \lambda_t^D$
	Positive	$\lambda_t^+ = \lambda_t^D$	$\lambda_t^+ = \min(\lambda_t^D, \lambda_t^{DN})$

3.2. ESS Modeling

The stochastic nature of WP and PV power poses significant challenges not only in grid integration but also in the decision-making process for the exploitation. Adequate usage of an ESS is a valuable solution to improve the matching of production with the compromised power or to develop arbitrage schemes, i.e., for taking economic advantage of the time shift of delivering power.

Particularly, time shift is of interest for WP and PV power producers that can store energy at periods of low market prices and sell this stored energy at a more favorable price period, i.e., a likely high price period. An ESS has a set of technical characteristics imposing, for instance, energy and power storage limits, efficiencies for charge and discharge processes. Additionally, binary variables are required to model these processes.

The modeling used in this paper for ESS assumes a null depth of discharge, i.e., all the stored energy can be discharged, and is typically the one describing a vanadium redox flow battery. This type of ESS is one of the most promising technology for energy management to mitigate the variation and intermittence of WP and PV power [63]. The modeling of the ESS is stated as follows:

$$0 \le e_{st}^{ESS} \le E^{ESS\max}. \tag{9}$$

In (9) the energy stored at scenario s and period t is limited to the maximum capacity of the ESS, which is an intrinsic characteristic of the ESS. Two binary variables to control the charge and discharge processes are introduced as follows:

$$k_{st}^{Ch} + k_{st}^{Di} \le 1; \tag{10}$$

$$0 \le p_{st}^{ChESS} \le P_{st}^{ChESS\max} k_{st}^{Ch}; \tag{11}$$

$$0 \le p_{st}^{DiESS} \le P_{st}^{DiESS\max} k_{st}^{Di}. \tag{12}$$

In (10) is imposed that the ESS cannot charge and discharge simultaneously. In (11) and (12) the charged and discharged power at scenario s and period t are limited to a maximum power allowed, respectively. The equation for the balance of energy of the ESS is stated as follows:

$$e_{st}^{ESS} = e_{st-1}^{ESS} + \eta^{ChESS} p_{st}^{ChESS} - \frac{1}{\eta^{DiESS}} p_{st}^{DiESS}. \tag{13}$$

In (13) e_{st}^{ESS} and e_{st-1}^{ESS} are the energy stored at scenario s and period t and period $t-1$, respectively; η^{ChESS} and η^{DiESS} are the efficiency of charging and discharging, respectively.

3.3. Thermal units modeling

The total operating cost OP_{sit} is given by the cost of operation of thermal units [64] stated as follows:

$$OP_{sit} = GC_{sit} + SUC_{sit} + SDC_{sit} z_{it} \quad \forall s, \quad \forall i, \quad \forall t. \tag{14}$$

In (14) the terms associated with unit i are respectively: the generation cost GC_{sit}, the start-up cost SUC_{sit}, and the shut-down cost SDC_{sit}. The generation cost GC_{sit} is stated as follows:

$$GC_{sit} = A_i u_{sit} + b_{sit} \quad \forall s, \quad \forall i, \quad \forall t. \tag{15}$$

In (15) the two terms are respectively the fixed cost and the variable cost of unit i. The variable cost of a thermal unit is typically formulated as a quadratic function, but to use MILP the variable cost is reformulated as piecewise linear function stated as follows:

$$b_{sit} = \sum_{l=1}^{L} F_i^l \delta_{sit}^l \qquad \forall s, \quad \forall i, \quad \forall t; \tag{16}$$

$$p_{sit} = P_i^{min} u_{sit} + \sum_{l=1}^{L} \delta_{sit}^l \qquad \forall s, \quad \forall i, \quad \forall t \tag{17}$$

$$(T_i^1 - P_i^{min}) t_{sit}^1 \le \delta_{sit}^1 \qquad \forall s, \quad \forall i, \quad \forall t; \tag{18}$$

$$\delta_{sit}^1 \le (T_i^1 - P_i^{min}) u_{sit} \qquad \forall s, \quad \forall i, \quad \forall t; \tag{19}$$

$$(T_i^l - T_i^{l-1}) t_{sit}^l \le \delta_{sit}^l \qquad \forall s, \quad \forall i, \quad \forall t, \quad \forall l = 2, \dots, L-1; \tag{20}$$

$$\delta_{sit}^l \le (T_i^l - T_i^{l-1}) t_{sit}^{l-1} \qquad \forall s, \quad \forall i, \quad \forall t, \quad \forall l = 2, \dots, L-1; \tag{21}$$

$$0 \le \delta_{sit}^L \le (P_i^{max} - T_i^{L-1}) t_{sit}^{L-1} \qquad \forall s, \quad \forall i, \quad \forall t. \tag{22}$$

In (16) the variable cost is given as the sum of products of the slope F_i^l by power δ_{sit}^l of the segment. In (17) the power of unit i is given by the minimum power generation plus the sum of the segment power. The binary variable u_{sit} ensures that if the unit is in the state offline, the power is null. In (18)–(22) the limits are set for the power of the segments. The start-up costs SUC_{sit} is typically formulated as an exponential, but to use MILP the variable cost is reformulated as stair wise function as follows:

$$SUC_{sit} \ge K_i^{\beta} \left(u_{sit} - \sum_{r=1}^{\beta} u_{sit-r} \right) \qquad \forall s, \quad \forall i, \quad \forall t. \tag{23}$$

In (23), the expression in parentheses determines if a start-up has occurred, i.e., if a start-up occurs, then the expression is equal to 1, implying that the unit has been in the state offline in the β preceding periods. The power generated for a unit i is stated as follows:

$$P_i^{min} u_{sit} \le p_{sit} \le p_{sit}^{max} \quad \forall s, \quad \forall i, \quad \forall t; \tag{24}$$

$$p_{sit}^{max} \le P_i^{min} (u_{sit} - z_{sit}) + SDz_{sit} \quad \forall s, \quad \forall i, \quad \forall t; \tag{25}$$

$$p_{sit}^{max} \le p_{sit}^{max} + RUu_{sit} + SUy_{sit} \quad \forall s, \quad \forall i, \quad \forall t; \tag{26}$$

$$p_{sit-1} - p_{sit} \le RDu_{sit} + SDz_{sit} \quad \forall s, \quad \forall i, \quad \forall t. \tag{27}$$

In (24) the p_{sit} is the power of unit i at period t, which is limited by the maximum power p_{sit}^{max} of unit i at period t. In (25)–(26) the maximum power p_{sit}^{max} is feasible if satisfy the constraint regarded with the actual capacity of unit i, the start-up and shut-down ramp rate limits and the ramp-up limit of the unit. In (25)–(27) the relation between the start-up and shut-down variables of unit i is given in function of the binary variables. The minimum up time constraints are stated as follows:

$$\sum_{t=1}^{N_i} (1 - u_{sit}) = 0 \qquad \forall s, \quad \forall i; \tag{28}$$

$$N_i = \min\{T, (UT_i - U_{si0})\, u_{sit}\}; \tag{29}$$

$$\sum_{t=k}^{k+UT_i-1} u_{sit} \ge UT_i y_{sit} \qquad \forall s, \quad \forall i, \quad \forall k = N_i + 1 \dots T - UT_i + 1; \tag{30}$$

$$\sum_{t=k}^{T} (u_{sit} - z_{sit}) \ge 0 \quad \forall s, \quad \forall i, \quad \forall k = T - UT_i + 2 \dots T. \tag{31}$$

In (28) the unit is imposed to remain in the online state for a specific number of periods in regard of the initial state. In (30) a start-up implies being online by at least UT_i periods. In (31) the minimum up time is imposed. The minimum down time the constraints are stated as follows:

$$\sum_{t=1}^{J_i} u_{sit} = 0 \qquad \forall s, \quad \forall i, \quad \forall t; \tag{32}$$

$$J_i = \min\{T, (DT_i - s_{si0})(1 - u_{sit})\}; \tag{33}$$

$$\sum_{t=k}^{k+DT_i-1} (1 - u_{sit}) \ge DT_i z_{sit} \quad \forall s, \quad \forall i, \quad \forall k = J_i + 1 \dots T - DT_i + 1; \tag{34}$$

$$\sum_{t=k}^{T} (1 - u_{sit} - z_{sit}) \ge 0 \quad \forall s, \quad \forall i, \quad \forall k = T - DT_i + 2 \dots T. \tag{35}$$

In (32)–(34) the unit is imposed to satisfy the down time constraint. In (35) the minimum down time is imposed, i.e., the unit must be down during at least the minimum number of down periods. The constraints on the binary variables are stated as follows:

$$y_{sit} - z_{sit} = u_{sit} - u_{sit-1} \quad \forall s, \quad \forall i, \quad \forall t; \tag{36}$$

$$y_{sit} + z_{sit} \leq 1 \quad \forall s, \quad \forall i, \quad \forall t. \tag{37}$$

In (36)–(37) the constraints on the start-up and shut-down variables of the thermal units are imposing that start-up and shut-down are not simultaneously feasible. The total power generated by thermal units is stated as follows:

$$p_{st}^{Ther} = \sum_{i=1}^{I} p_{sit} \qquad \forall s, \quad \forall t. \tag{38}$$

Although not explicitly mentioned in the above constraints any linear constraint in continuous variables is possible to be considered, for instance, a local constraint in the power of a group of thermal units due to fossil fuel or an emission restriction on the operation of the group of thermal units.

4. Problem formulation

4.1. Aggregated formulation

The goal of the profit-based stochastic unit commitment problem aggregating thermal units, renewable energy, and ESS is to deliver an enhancing management information system for maximizing the expected profit of the bidding in the DAM and without discarding that the deposition of dust influences the expected profit. So, this influence must be considered in the problem formulation. The tilt angle of the panels is in practice correlated with the amount of density of dust on the surface of the panel. This amount of dust density is in this paper emulated by a factor $\alpha \in [0, 1]$ given from historical data shaping the above correlation, reducing the available power on the PV power scenarios. Therefore, the value of p_{st}^{PV} characterizing the power of the PV power scenarios is replaced by $p_{st}^{PV}\alpha$.

The objective function is stated as follows:

$$\max PROFIT = \sum_{s=1}^{N_s} \sum_{t=1}^{T} \frac{1}{N_s} (REV_{st} + IMB_{st} - COST_{st}). \tag{39}$$

In (39) REV_{st}, IMB_{st} and $COST_{st}$ are the revenue associated with the scenario s period t, the imbalance contribution for the profit incurred with the scenario s period t, and the total generation costs in the scenario s period t, respectively. The imbalance contribution can have positive or negative values. If the value of the imbalance contribution is positive, then the contribution is in favor of the revenue, if negative is a loss of revenue. The sum is over the total number of scenarios N_s and the scenarios are considered as equiprobable ones, i.e., the probability of each scenario is $1/N_s$. But the formulation can be easily adapted if different probabilities are imposed for the scenarios. The revenue considered in (39) is a per scenario one, i.e., a revenue of participation in the DAM. This revenue for scenario s and period t is stated as follows:

$$REV_{st} = p_{st}^{Total} \lambda_{st}^{D}. \tag{40}$$

In (40) p_{st}^{Total} and λ_{st}^{D} are the total bid in the DAM and the DAM price in the scenario s and period t, respectively. This contribution is a per scenario revenue/cost due to the participation in the balancing market stated as follows:

$$IMB_{st} = d_{st}^{+} \lambda_{st}^{D} PR_{st}^{+} - d_{st}^{-} \lambda_{st}^{D} PR_{st}^{-}. \tag{41}$$

In (41) d_{st}^{+} and d_{st}^{-} and PR_{st}^{+} and PR_{st}^{-} for the scenario s at a period t are the positive and negative power deviations and down imbalance price ratios, respectively. If there is a positive imbalance the first term of (41) has a non-null value, while the second has a null value; if there is a negative imbalance the first term of (41) has a null value, while the second one a non-null value.

Since normally is assumed that the costs of operation of the renewables, the WP or PV power, or the ESS are negligible, the costs in (39) are costs only due to the thermal unit operations. The total generation cost for the scenario s period t is stated as follows:

$$COST_{st} = \sum_{i=1}^{I} OP_{sit}. \tag{42}$$

In (42) OP_{sit} is the operating costs of thermal unit i for the scenario s at a period t.

The goal of maximizing the expected profit is subjected to the following constraints.

(a) *Energy Bid Constraint*

The energy bid must satisfy the modeling constraint as follows:

$$0 \leq p_{st}^{Total} \leq \sum_{i=1}^{I} p_{sit}^{\max} + P^{W\max} + P^{PV\max} + P^{DiESS\max} \qquad \forall s, \forall t. \tag{43}$$

In (43) the bid for the scenario s at a period t p_{st}^{Total} is imposed to be never greater than the sum of the maximum powers of the thermal units for the scenario s at a period t, the WP, the PV power, with the maximum discharged power of the ESS.

(b) *Imbalance Constraints Considering Dust*

The imbalance constraints to take in consideration the dust effect satisfies the proposed modeling constraint as follows:

$$d_{st} = p_{st}^{Ther} + P_{st}^{W} + P_{st}^{PV}\alpha - p_{st}^{Total} \quad \forall s, \ \forall t, \ \forall \alpha \in [0, 1]. \tag{44}$$

In (44) α is a factor associated with the effect of dust density, i.e., a factor that echoes the value of PV power reduced due to the deposition of dust. The imbalance in (44) further satisfies a constraint given as the difference between two contributions said to be the positive and negative imbalance terms. Hence, the imbalance is stated as follows:

$$d_{st} = d_{st}^{+} - d_{st}^{-} \quad \forall s, \ \forall t. \tag{45}$$

In (45) the formulation ensures that only one of the imbalances has a non-null value. The positive and negative imbalances are bounded by the constraints stated as follows:

$$0 \leq d_{st}^{+} \leq p_{st}^{g} + P_{st}^{W} + P_{st}^{PV}\alpha \quad \forall s, \ \forall t, \ \forall \alpha \in [0, 1]; \tag{46}$$

$$0 \leq d_{st}^{-} \leq \sum_{i=1}^{I} p_{sit}^{max} + P^{W\max} + P^{PV\max} + P^{DiESS\max} \qquad \forall s, \forall t. \tag{47}$$

(c) *Bidding Curves Constraint*

Bidding curves are a useful aid for taken decisions and are normally subjected to a modeling constraint as follows:

$$\left(p_{st}^{Total} - p_{s-1t}^{Total}\right)\left(\lambda_{st}^{D} - \lambda_{s-1t}^{D}\right) \geq 0 \qquad \forall s, \ \forall t. \tag{48}$$

In (48) are imposed that the bidding curves must satisfy the usual management requirement of the non-decreasing condition constraint.

4.2. Disaggregated formulation

The disaggregated formulation for a specific technology is performed by setting all the parameters and variables related to the remaining technologies to zero in the formulation (39)–(48).

Table 4
Thermal units.

Unit	$P_i^{\min}$ (MW)	$P_i^{\max}$ (MW)	UT_i (h)	DT_i (h)	SU_i (MW)	SD_i (MW)	RU_i (MW/h)	RD_i (MW/h)	A_i (€/h)	SDC_i (€/h)
U1	70	125	5	4	100	95	45	40	2900	170
U2	60	125	5	3	90	80	55	55	3060	120

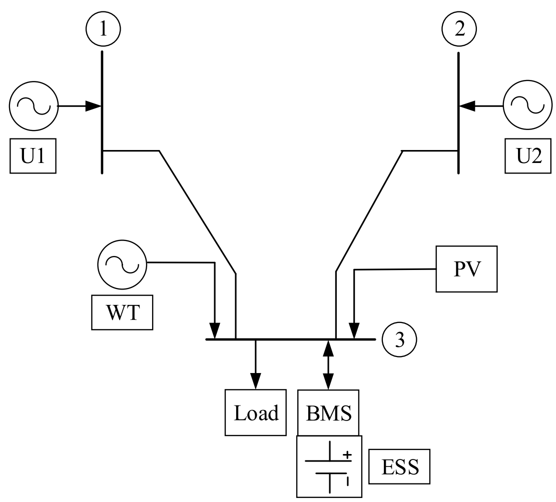

Fig. 2. Aggregation of wind system, PV system, thermal units, and ESS.

For instance, the disaggregated formulation for WP is stated as follows:

$$\max PROFIT = \sum_{s=1}^{N_s} \sum_{t=1}^{T} \frac{1}{N_s}(REV_{st} + IMB_{st}). \tag{49}$$

where

$$REV_{st} = P_{st}^{Total} \lambda_{st}^{D}. \tag{50}$$

$$IMB_{st} = d_{st}^{+} \lambda_{st}^{D} PR_{st}^{+} - d_{st}^{-} \lambda_{st}^{D} PR_{st}^{-}. \tag{51}$$

subject to

$$0 \leq p_{st}^{Total} \leq P^{W\max}. \tag{52}$$

$$d_{st} = P_{st}^{W} - p_{st}^{Total} \quad \forall s,\ \forall t. \tag{53}$$

$$d_{st} = d_{st}^{+} - d_{st}^{-} \quad \forall s,\ \forall t. \tag{54}$$

$$0 \leq d_{st}^{+} \leq P_{st}^{W} \quad \forall s,\ \forall t. \tag{55}$$

$$0 \leq d_{st}^{-} \leq P^{W\max}, \quad \forall s,\ \forall t. \tag{56}$$

$$(p_{st}^{Total} - p_{s't}^{Total})(\lambda_{st}^{D} - \lambda_{s't}^{D}) \geq 0 \quad \forall s,\ s', \quad \forall t. \tag{57}$$

5. Case studies

The aggregator manages a WP, a PV power, thermal unit power with an ESS as shown in Fig. 2.

The case studies are:

Case 1#–Analysis of the profitability of the aggregation;

Case 2#–Analysis of the impact of dust accumulation on the profitability of the aggregation.

Table 5
Piecewise linear approximations for the variable cost.

Unit	T_i^1 (MW)	T_i^2 (MW)	F_i^1 (€/MWh)	F_i^2 (€/MWh)	F_i^3 (€/MWh)
U1	100	115	33.22	34.81	35.61
U2	90	115	43.98	39.77	42.12

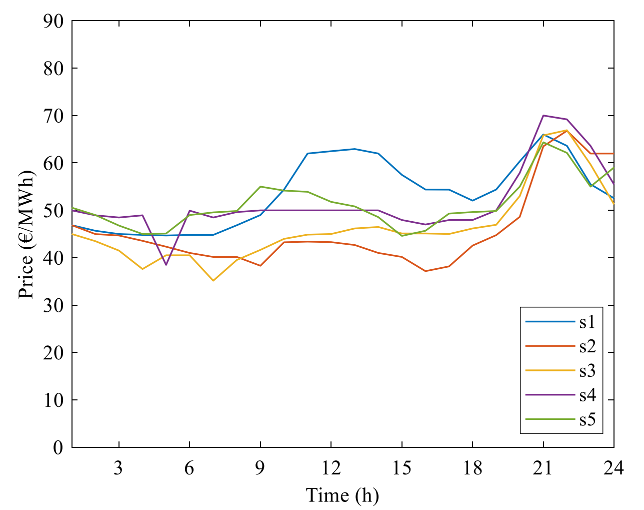

Fig. 3. DAM price scenarios.

5.1. Input data

The aggregator owns two thermal units having minimum and maximum power, ramp up/down rates, start-up and shut-down values, minimum up/down time, fixed and shut-down costs as shown in Table 4.

The variable costs of the thermal units are given by an approximation given by piecewise linear function with the parameters as shown in Table 5.

The start-up costs of thermal units given by an approximation given by a stairwise function with the parameters as shown in Table 6.

The rated power of the WP system and the PV power system is 100 MW each. The ESS is considered a vanadium redox flow battery with the data given in Table 7.

The scenarios for market prices, WP, and PV power are reported in Refs. [65–67]. The case study is on an hourly basis for a time horizon of 24 h.

The simulations of the case studies are implemented in GAMS and solved by the solver CPLEX 12.1, using a 4-GHz processor with 4-GB of RAM. The number of equations, continuous and binary variables and the CPU time are reported in Table 8.

The case study due to the uncertainty has 625 scenarios of data in what concerns the aggregation bidding. These scenarios are as follows: 5 scenarios for DAM prices, 5 scenarios for imbalances prices, 5 scenarios for WP and 5 scenarios for PV power.

The DAM price scenarios are in Fig. 3.

Fig. 3 shows that the price for the scenarios with an exception for scenario 2 show a tendency to have more favorable values in the range from the 6 h to the 24 h. After the 20 h, the prices have

Table 6
Stairwise approximations for the start-up cost.

Unit capacity (MW)	K_i^1	K_i^2	K_i^3	K_i^4	K_i^5	K_i^6	K_i^7	K_i^8	K_i^9	K_i^{10}
<125	654	1347	1896	2254	2533	2684	2733	2767	2813	2853
≥125 and ≤215	1046	2155	3034	3606	4053	4294	4373	4427	4501	4565

Table 7
Renewable energy and ESS data.

System	Minimum power output (MW)	Maximum power output (MW)	Charge efficiency	Discharge efficiency
Wind	0	100	–	–
PV	0	100	–	–
ESS	0	100	0.90	0.90

Table 8
Number of equations and variables.

	Equations	Continuous variables	Binary variables	CPU time (s)
Wind disaggregated	5 275	4 921	0	6
PV disaggregated	5 275	4 921	0	6
Thermal disaggregated	35 947	12 423	1 200	1800
Wind-PV-Thermal-ESS aggregated	899 087	288 549	1 320	2400

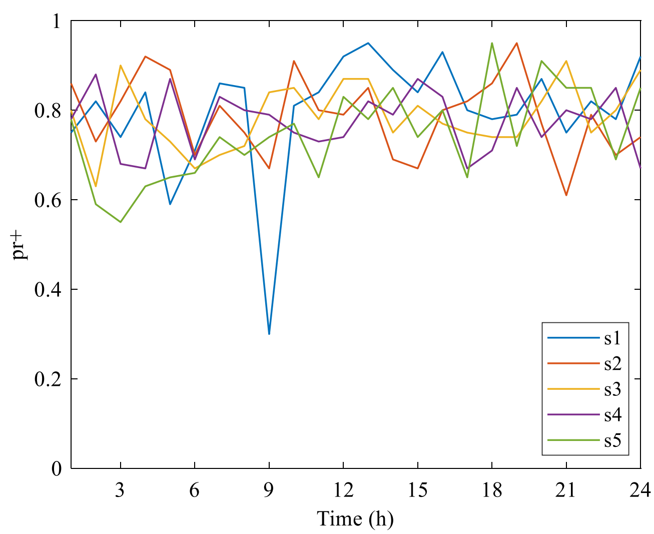

Fig. 4. Positive imbalance price ratios.

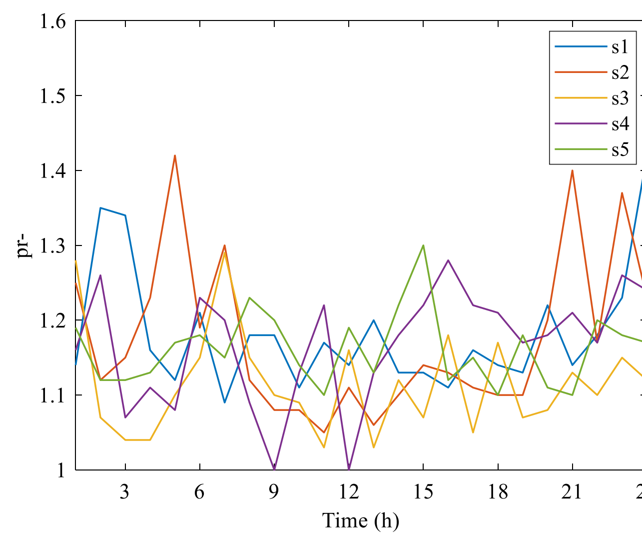

Fig. 5. Negative imbalance price ratios.

in average higher values and smaller dispersion. Consequently, if available WP and PV power are expected to contribute for storage into the ESS before the 6 h and discharge after 20 h. The positive imbalance price ratios for the scenarios are in Fig. 4.

In Fig. 4 the positive imbalance price ratios show a tendency of almost the same value of dispersion at each hour with exceptions at 3 h and more significantly at 9 h due to the unfavorable values of scenario 5 at 3 h and scenario 1 at 9 h, respectively. Consequently, from this data a positive imbalance is not favored to happen at any particular hour, i.e., almost all hours are equivalent in what regards the possibility of going into a positive imbalance.

The negative imbalance price ratios scenarios are in Fig. 5.

In Fig. 5 the negative imbalance price ratios show a tendency to be lesser penalizing from 9 h to 15 h, particularly the scenario 4 at 9 h and 12 h is most favorable for going into underproduction. This tendency is relevant for both aggregation and disaggregation. So, the main difference to be expected between aggregation and disaggregation schedule is due to the schedule of the ESS, regarding the influence of PV power and WP or not, respectively. The WP scenarios are in Fig. 6.

In Fig. 6 the scenario 1 is the one with less time variability power and almost less power than all other scenarios in a significative range of the time horizon. The WP scenarios show a tendency to have more favorable values from the 15 h to 20 h. The WP is eventually expected to contribute for storing energy in the ESS before the 9 h due to the tendency of lower favorable DAM price scenarios before this hour as shown in Fig. 3.

The PV power scenarios are in Fig. 7.

In Fig. 7 the PV power scenarios s1 and s3 model the data of solar power associate with attenuation due to sky significant clouding roughly from 11 h to 18 h. Scenario s3 is the one more affected from 15 h to 16 h due to very dark clouds. But in general, the PV power scenarios have power in the range of favorable DAM prices, from 6 h to 21 h, allowing anticipating that the storage of PV power in this range is not to be expected. Notice that the PV power uncertainty is mainly due from scenario 1 and 3 realizations and mainly due from 11 h to 16 h. Also, notice that the PV power uncertainty is less significant than the one for the WP.

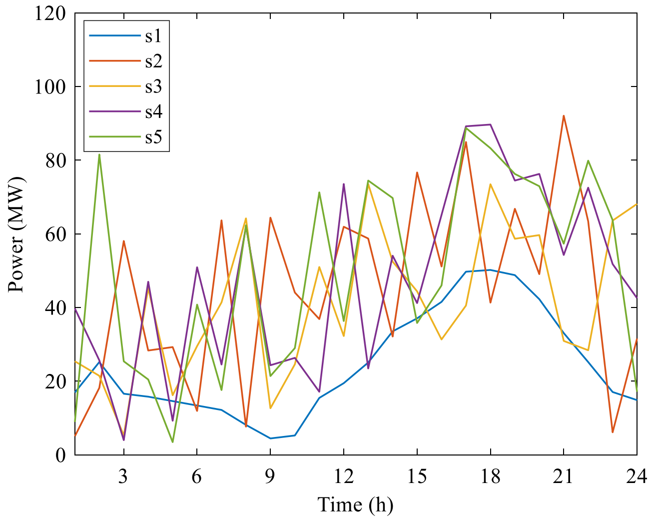

Fig. 6. WP scenarios.

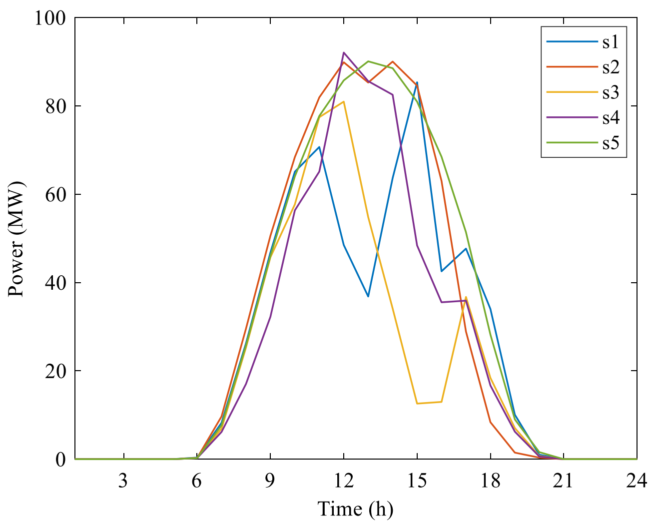

Fig. 7. PV power scenarios.

5.2. Case 1# — analysis of the profitability of aggregation

The optimal hourly bids for the disaggregation and the aggregation are in Fig. 8.

In Fig. 8 the bid for aggregation at 5 h is significantly smaller than the disaggregated one and at 21 h is greater than the disaggregated one, because of the tendency for lesser favorable price scenarios before 6 h and more favorable after this hour allowing to do arbitrage, i.e., taking economic advantage of the time shift of power. As envisaged WP is stored in the ESS before 6 h, in fact at 5 h, and ESS discharges at 21 h. Although the bids have smaller differences in other hours, the main difference between aggregation and disaggregation is due to the schedule of the ESS, bringing more profitable management with aggregations. This case study shows an analysis of the profitability of aggregation, i.e., infer in what manner the aggregation of all the power sources results is prone to deliver an expected profit higher than the disaggregation one. In this case study, the factor $\alpha \in [0, 1]$ used to emulate the PV power reduction due to dust accumulation is considered 1, i.e., $\alpha = 1$. The optimal hourly bids for specific scenarios are in Fig. 9.

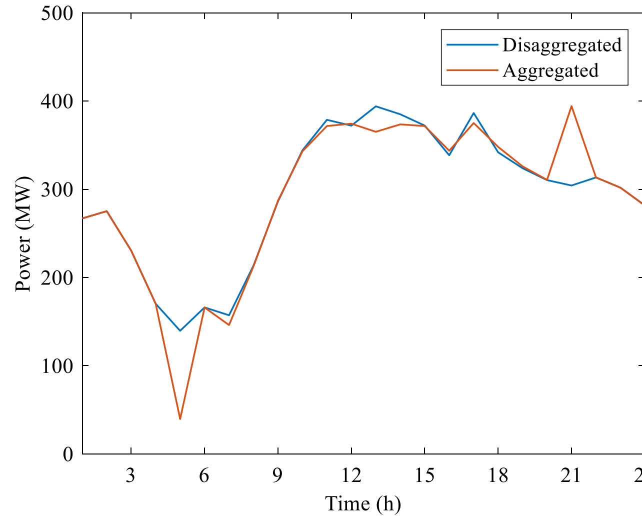

Fig. 8. Optimal hourly bids.

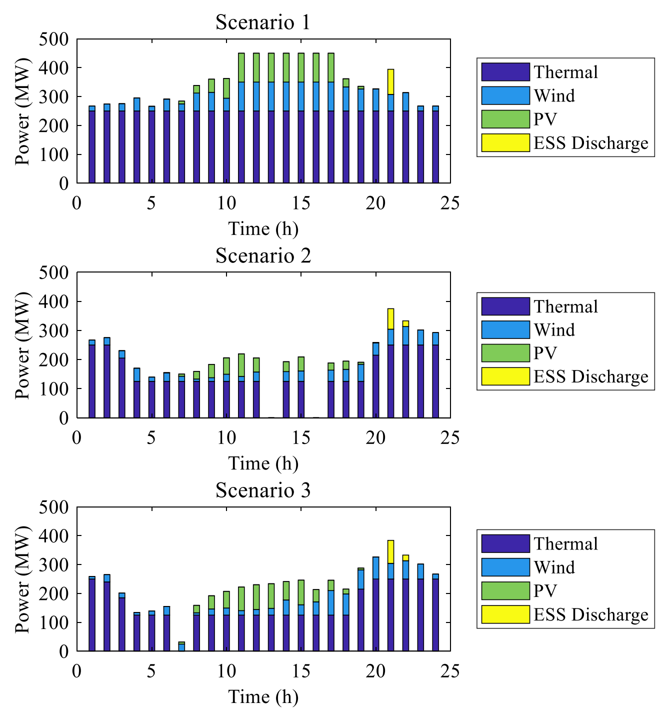

Fig. 9. Optimal hourly bids for price scenarios 1, 2 and 3.

Fig. 9 shows in scenario 1 that thermal units are at full power due to the favorable prices. While for scenarios 2 and 3, thermal units are not at full power. In some hours the thermal units are at the minimum power and even shutdowns are scheduled. Notice that in all these scenarios the ESS is scheduling to discharge at the 21 h, due to the favorable prices. So, the schedule of the ESS seems to be mostly governed by the prices. The wind scenarios tend to have high values of power between 16 h and 22 h while the PV scenarios tend to have high values of power between 10 h and 16 h. In Fig. 9 bids are computed for $5\times5\times5\times1 = 125$ scenarios, i.e., uncertainty on the DAM prices is discarded: with the scenario 1, the hourly bids are high due to high values of the prices, such that, all thermal units are at full power and between 11 h and 17 h the total capacity of the production is offered, the ESS is discharging at 21 h due to a high value price; with the scenario 2, the hourly bids are moderate between 3 h and 20 h

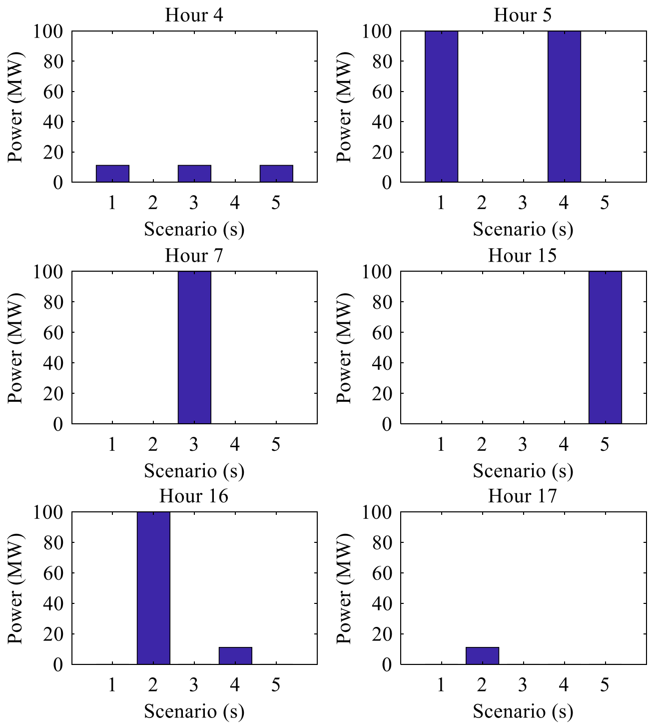

Fig. 10. Charged power of the ESS.

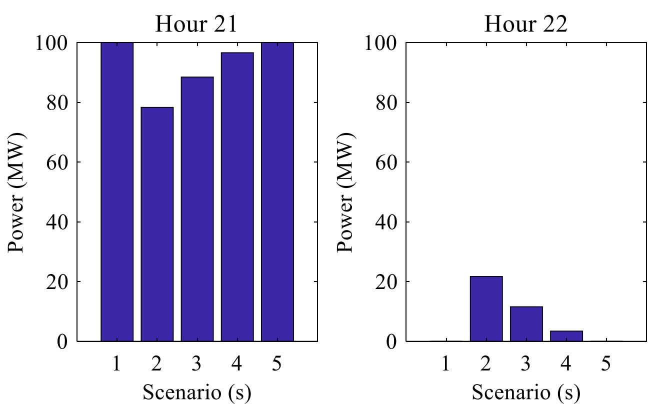

Fig. 11. Discharged power for selected scenarios.

due to low prices. Between 21 h and 22 h, the ESS is discharging due to high prices. This scenario schedules no offering at 13 h and 16 h, due to low prices and low positive imbalance prices, i.e., a defensive attitude; with the scenario 3, the hourly bids are moderate between 3 h and 19 h. Only unit 1 is in production between 4 h and 18 h and WP and PV power contribute with low powers. At 7 h the power is low due to a decrease in the prices. The charging of the ESS as a function of the prices of the five scenarios is shown in Fig. 10.

In Fig. 10 at 5 h the ESS is significantly charging for scenarios 1 and 4 due to low prices, low positive imbalance and high negative imbalance prices; at 16 h, the ESS charges at full power for scenario 2 and at lower power for scenario 4; at 17 h the ESS has a small charge under the scenario 2, again, due to a low price. The discharged power of the ESS is in Fig. 11.

Fig. 11 shows that at 21 h the ESS is discharging in all the 5 scenarios, due to high prices. While at 22 h the discharge is less and there is no discharging for scenarios 1 and 5 since the respective prices are lower than the ones in 21 h. Hence, if only one scenario is chosen for the price the bid is not in accordance with the uncertainty on prices, i.e., the bid is not tuned in what regards the achievement of convenient operation under uncertainty on prices. The consideration of all uncertainties in the aggregation allows for more appropriate bidding. A comparison of bidding curves for disaggregated and aggregated bidding at 4 h, 5 h, 6 h, 17 h, 18 h, and 21 h are in Fig. 12.

In Fig. 12 the bidding curves allow to unveil a tendency between disaggregation and aggregation: disaggregation has high power for low prices and low power for high market prices in comparison with aggregation, respectively. The aggregation has higher profit, since, the ability to coordinate production can deliver a better bid. For instance, the ESS discharge at 21 h, allows an increase of power bids delivering better profit. The unit commitment for disaggregation and aggregation are in Fig. 13.

In Fig. 13 unit 1 remains online 24 h in both aggregation and disaggregation and unit 2 is offline in all scenarios at 0 h in aggregation unit 2 is offline in 14 h, 15 h, 16 h, 17 h, and 18 h in scenario 3 in comparison with the disaggregation. This is due to the low prices in scenario 3 and the disadvantage cost of unit 2 in comparison with unit 1. Hence, the aggregation can reduce the calls of thermal units and in any case is never worse than the disaggregation. The profit and the relative gain are in Table 9.

Table 9
Expected profit for disaggregation and aggregation and relative gain.

Configuration	Expected profit (k€)	Gain (%)
Wind disaggregated	47.4	–
PV disaggregated	28.9	–
Thermal disaggregated	41.8	–
Wind-PV-Thermal disaggregated	118.1	–
Wind-PV-Thermal aggregated	120.0	1.65
Wind-PV-Thermal-ESS aggregated	121.4	2.76

Table 9 shows that: the expected profit of aggregation without the ESS is 1.65% higher than the disaggregated one; the expected profit with aggregation having the ESS is 2.76% higher than the disaggregated one, i.e., almost 1.1% higher in comparison to the aggregation without the ESS. The 2.76% higher per day implies in a year an augmented in the expected profit of almost 1.2×10^3 k€.

5.3. Case 2# - analysis of the impact of dust accumulation on the profitability of aggregation

The profit, the relative gain, the imbalance cost and the relative increment as a function of the dust parameter α are in Table 10.

Table 10 shows that while the profit can decrease about by 10% with a dust effect at 40%, the imbalance cost is increased about by 23%. The unavailability of PV power implies by simulation a decrement in the profit of about 25.0%. So, the dust effect influences significantly the production of the PV modules. Loss of profit accumulated during several days can be significative higher than the cost of removing dust, so that removing must be scheduled in due time. The profit and the imbalance cost as a function of the dust parameter α are in Fig. 14.

Fig. 14 shows that the decrement in PV power due to the dust effect is in line with the increment in the imbalance cost and the decrement in the profit. Also, the decrement in PV power means an increment in thermal power in terms of share of renewables and consequently an increment in the greenhouse gas emissions. Also, the PV power decrement reduces the ability of PV to contribute to the lessening WP volatility, implying the increment of imbalance cost. So, the decrement in PV power due to the dust effect is not advisable both technically and economically. This case study shows the analysis of the impact of dust accumulation

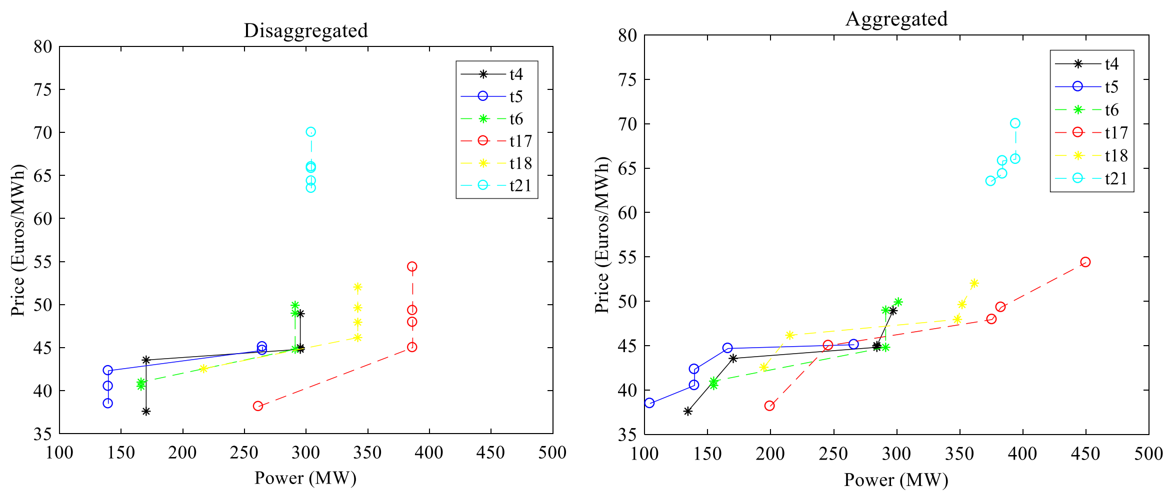

Fig. 12. Optimal bidding curves: left — disaggregated; right — aggregated.

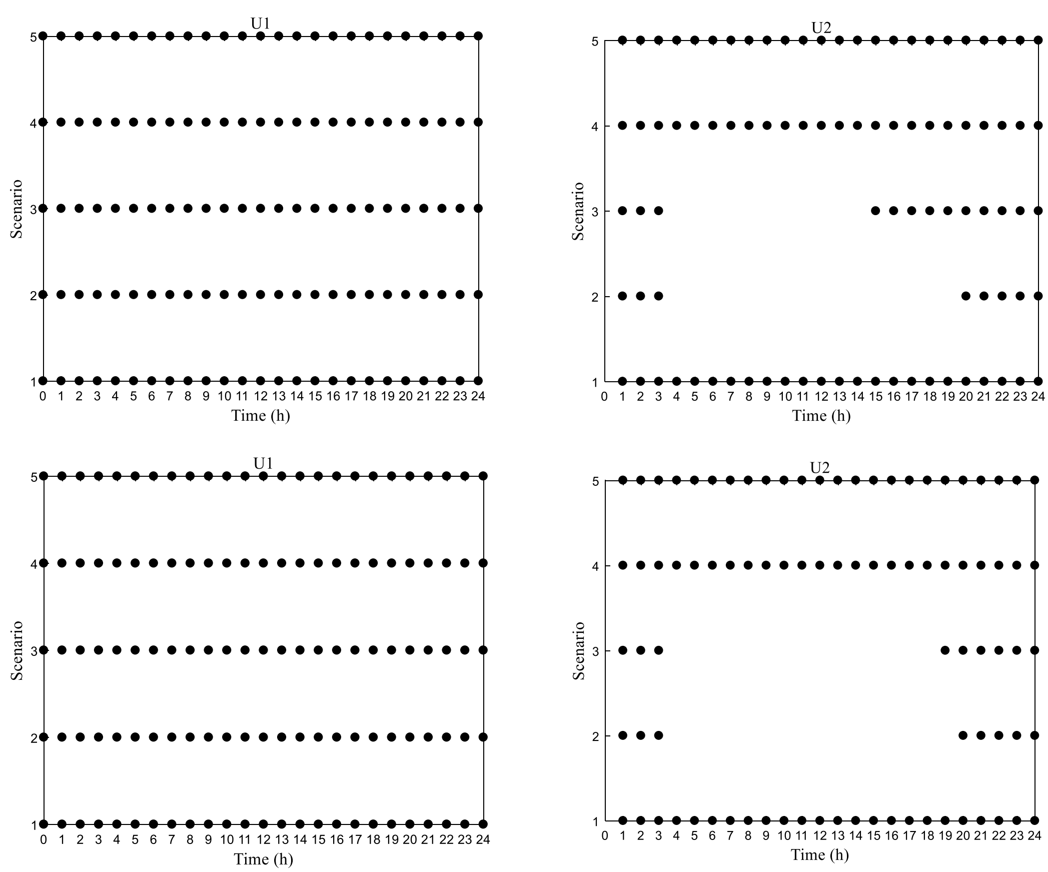

Fig. 13. Hourly self-scheduling of thermal units for the scenarios: top: disaggregated; bottom: aggregated.

Table 10
Profit, relative decrement, imbalance cost, and the relative increment as a function of the dust parameter α.

Dust level	$\alpha \in [0, 1]$	Profit (k€)	Decrement (%)	Imbalance cost (k€)	Increment (%)
Dust-free	1.0	121.4	–	10.8	–
Dust-10%	0.9	118.5	2.38	11.4	5.6
Dust-20%	0.8	115.6	4.77	12.0	11.1
Dust-30%	0.7	112.7	7.16	12.6	16.7
Dust-40%	0.6	109.8	9.55	13.3	23. 1

on the profitability of aggregation, i.e., infer if the PV power reduction due to dust accumulation results in the reduction of profit of the aggregator. In this case study, the dust parameter$\alpha \in [0, 1]$ that emulates the PV power reduction due to dust accumulation is a changeable value. The 5 dust levels considered are: dust-free ($\alpha = 1$), i.e., the PV power is not affected; dust-10% ($\alpha = 0.9$),

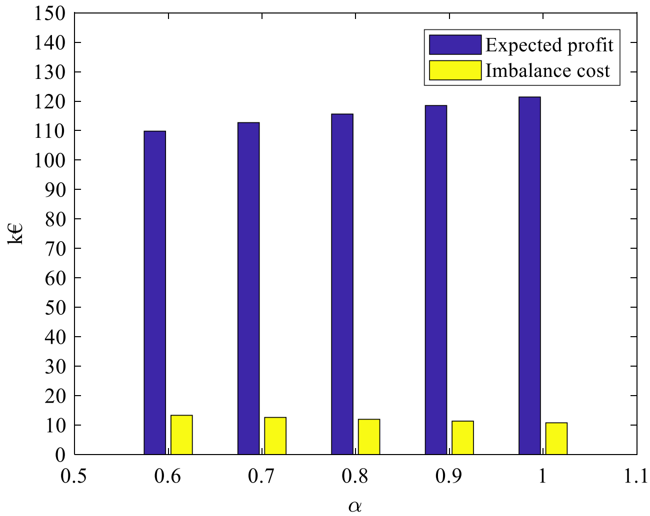

Fig. 14. Profit and imbalance cost as a function of the dust parameter α.

i.e., the PV power is reduced by 10%, and so on. The considered values are based on experimental results of power reduction [14–18]; due to the dust effect.

6. Conclusion

The change of the power sector from publicly regulated to a market-based industry brought the need for a new unit commitment problem known as the profit-based unit commitment problem. Also, concerns about sustainability and a healthy environment brought the need for the exploitation of renewable variable sources of energy. A stochastic approach for this unit commitment in what regards bidding in a DAM addressed for aggregation of WP, PV power, and thermal power with an ESS is the main purpose of the paper. The total operating cost for the aggregation is due to the operation with thermal units, and constraints model the technical characteristics of the power units and the ESS. The uncertainties regarding the availability of WP, PV power, and market prices are input data. The formalization of the problem is of the type of a mathematical programming problem based on a stochastic approach formulated as a mixed-integer linear programming problem. The convenient and adequate usage of an ESS is a valuable benefit, known to be an advantage not only in matching the production with the compromised power in a market, but also allowing for arbitrage schemes. But, the model dependence of the schedule for charge or discharge of the ESS must consider the uncertainty due to market prices. The influence of uncertainty of the market prices on the ESS schedule is in favor of being an opportunity to drive the capability to allow for arbitrage schemes. This influence is discernible and shown to deliver an increase in the power offer, improving the profit.

The decrement in PV power due to the dust effect diminishes the contribution in the lessening WP volatility, implying an increment of imbalance cost, subjecting the aggregator to a decrement in the profit. Also, the decrement in PV power in the mix of productions of a DAM implies the need to call more thermal power, and consequently, augments the greenhouse gas emissions. Dust must be removed from PV modules in due time not only to avoid losses of PV power, that can be quantified in what regards bidding in a DAM by the proposed unit commitment but also to contribute to a healthy environment and as sustainable development.

CRediT authorship contribution statement

I.L.R. Gomes: Investigation, Software, Writing - original draft. **R. Melicio:** Conceptualization, Methodology, Validation, Writing - review & editing. **V.M.F. Mendes:** Conceptualization, Methodology, Validation, Writing - review & editing.

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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