A Two-Stage Stochastic Optimization Approach to Aid in Decision Making Under Uncertainty for a Variable Resource Generator Participating in a Sequential Energy Market

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Abstract

Decisions for a variable renewable resource generator’s commitment in the energy market oftentimes must be made ahead of time when little information is available about availability and market prices. Much research has been published recommending various frameworks for addressing this issue, however, they are not comprehensive since they do not take into consideration all markets a producer can participate in. Moreover, current stochastic programming models do not allow for uncertainty data to be updated as more accurate information becomes available. In this work, we propose two decision-making frameworks for a wind energy generator participating in day-ahead, intraday, reserve, and balancing markets. The first is a stochastic two-stage scenario-based approach, and the second is a series of four two-stage stochastic optimization models wherein results from each model feed into each subsequent model allowing for scenarios to be updated as more information becomes available to the decision-maker. This improves the quality of the decisions, which in turn leads to improved profitability. The simulation ran resulted in the multi-phase framework performing better than the single-phase in every run, and a mean average increase of profit of 51%. The model aids in better decision making, addresses uncertainty related to variable resource generators and optimizes the return on investment.

Keywords: Wind energy, Variable Renewable Resource Generator, sequential energy market, two-stage stochastic optimization, data-driven scenarios, data uncertainty

1. Introduction

Renewable energy has started to play a more prominent role in the electricity markets; however, additional complexity arises when considering Variable Renewable Resource Generators (VRRGs) due to the variable nature of the available resource. Unlike other renewable resources, such as biogas and geothermal, with VRRGs such as wind and solar photovoltaic, the amount of the resource available is variable and dependent on nature. It cannot be controlled and is difficult to predict. Moreover, most electricity markets around the world demand that the amount of energy sold by a generator be committed
ahead of time before accurate information is available. As such, decision making becomes a complex task. In this work we consider a wind energy farm.

Typically, an energy producer in the European energy market must make commitments of how much energy it will buy and sell one day prior to the actual buying and selling of said energy. The energy producers are then subject to monetary penalties if they deviate from their committed schedules. In order to alleviate the issue of inaccurate information, most electricity markets are designed in a sequential manner where the generator can remedy discrepancies between energy committed and energy available when more information is made available and throughout the day where energy is being sold. However, this of course comes with an added cost since market prices become less favorable from the producer’s point of view. Therefore, the energy producer must be able to make as accurate forecasts of energy availability ahead of time, in addition to following the right strategy of knowing which market to participate in in order to make the most profit.

The pool market (PM) is made up of three different markets in which commitments can be sequentially updated. Pool market is where energy is traded on short term basis. It typically includes: (1) A day-ahead market (DAM), (2) adjustment markets, such as an Intraday Market (IDM), and (3) Balancing Markets (BM) [1]. Additionally, there are other markets such as the reserve and regulation markets to ensure secure system operation and energy delivery [1]. Note that these are not the same as the spot balancing market used for settlement of deviations for the W&SPP (Wind & Storage Power Plant); these are requirements by the system operator.

In this work, we consider the regulation market wherein up and down real-time load-following capability is provided to enforce continuous balance between production and consumption [1]. Regulation market (RGM) is typically cleared once a day on hourly basis and assigns production units the power bands to be used in real-time operation for load following [1].

The electricity market is usually regulated by a System Operator (SO), which has the role maintaining the reliability, security, stability, and quality of the power supply to the customers. Matching the supply and demand is vital for electrical grid operation and is termed “frequency regulation”. One method of frequency generation is requiring the generator to increase or decrease out by some amount. This is known as “regulation up” and "regulation down". Therefore, the generator must commit to removing capacity and to being able to produce extra power in the real-time market. This also adds an increased level of uncertainty for a generator.

Another way of overcoming the problem of uncertainty is using Energy Storage Systems (ESS). By using an ESS, excess energy can be stored and used later when natural resources are not available. However, ESS are expensive and do not always make up for the additional profit that the generator makes. As such, this work will also include an economic model to make decisions regarding the financial feasibility of installing an ESS to the plant. Research has shown the theoretical and practical significance of integrating storage to a wind farm, mainly for adding an arbitrage potential of WF-ESS participating in multistage spot EMs, and thus leading to a total profit improvement [2], [3].

Wind forecast errors are unavoidable and therefore WFs are forced to take corrective actions which are generally costly [3], [4]. To mitigate, we need to take uncertainty into consideration by using a stochastic approach, as well as make full use of the balancing and intraday markets. In this work, stochastic optimization is combined with machine learning methods. Machine learning has allowed data-driven analysis to benefit rule-based optimization in the application of power system optimization [5].
2. Literature Review

Stochastic programming has been used extensively in the literature to optimize the participation of renewable, non-renewable [6], [7], and combination energy generators in electricity markets around the world. In this literature we will explore various applications for stochastic optimization models that include schedule-related decision making for systems that include wind farms.

When it comes to planning energy generation for variable renewable energy generator, the variability can lead to a lot of uncertainty. Combined with stochastic programming, there are various methods combined with stochastic programming to deal with that uncertainty and increase reliability of the proposed solution. The model in Ref. [8] includes chance-constrained stochastic program features in a two-stage stochastic program. In Ref. [9] robust optimization techniques are used to represent the uncertainty through confidence bounds. Ref. [10], [11] results resulting from scenarios developed using various clustering techniques combined with LSTM-RNN MCC training. Ref. [12] uses scenario tree construction algorithms to successively reduce the number of nodes to reduce the computational burden and keep the problem tractable.

Another way of reducing the problem size, and thus the simulation time is through stochastic mixed integer programming (SMIP). For instance, Ref. [13] uses a stochastic mixed integer LP to aid decision making for a single renewable unit in the DAM while considering risk-hedging through Conditional Value at Risk. In Ref. [14] the SMIP’s first-stage involves network-constrained unit commitment in the base case and the second-stage investigates security assurance in system scenarios. The model would schedule reserves provided by DRPs and determine commitment states of generating units and their scheduled energy and spinning reserves in the scheduling horizon.

MILP are also commonly used for generation expansion planning such as the two-stage MILP frameworks developed in Ref. [15] and Ref. [16] to handle the uncertainty of the GEP problem. However, stochastic programming models can also be seen used to aid decision-making from perspectives other than that of a generator. In Ref. [17] a stochastic decision making framework is developed from the perspective of not a producer, but rather a local market operator and aggregator or prosumers. In ref [18] the problem is looked at from the perspective of an aggregator for electric vehicle charging stations. In ref [19] a two-sided two-stage optimization model simultaneously takes into account both the supply and the demand side of wind power to ensure stable consumption in the real-time market.

Due to the instability of wind power generation, most systems are a combination of wind energy with another power source. Ref [20], [21], [22] develop stochastic optimal distribution scheduling models for hybrid wind-solar systems, wherein system uncertainties also include those that impact solar plants such as irradiance. In ref [23] a coupling series of models is developing for seeking optimal hydropower and wind power strategies. Similarly in ref [24] a combination natural gas and wind power energy system is considered and modeled using a stochastic optimization.

One method of eliminating the negative characteristics of uncertainty for renewable energy power generation and making up for forecasting errors is through including a form of energy storage in the system [25]. Ref [26] and [2] looks at a hybrid power system consisting of WFs and batteries to co-optimize both the day-ahead offering and nominal real-time operating strategies of WF-ESS. In Ref [10] the analysis of the stochastic program includes a comparison of various sizes of energy storage systems such as batteries. Ref. [27] looks at an optimal bid submission in a day-ahead electricity market for the problem
of joint operation of wind with photovoltaic power systems having an energy storage device. In Ref. [28] rather than a battery, a hydro pumped storage units are considered in the formulation.

We see in many of the models the idea of co-optimizing the participation of a generator in both the day ahead as well as in the balancing market [2], [10], [29], however, it is also important to consider the participation of the generator in the reserve regulation market. In ref [11] a Long Short-Term Memory Recurrent Neural Network is designed to generate forecasts for regulation requirements. In ref [30] producers are encourage to use the reserve market to regulate short term-output by using some of the generation mismatch as regulation reserve services instead of appearing as energy imbalance in order to avoid paying penalties and increase profit. In refs [31], [32] reserve dispatch is considered using a risk-averse approach by minimizing the conditional value-at-risk (CVaR), however, the in ref [32], the model also considers the BM.

3. Contributions

None of the listed references include the day-ahead, intra-day, reserve, and balancing markets within a single framework. As such, there is still a potential for improving the participation of a renewable power generator within the power-market. Findings suggest that wind power plants that are active is day-ahead, real-time and reserve markets are able to increase profitability [10], [30], [33]. The generator can not only increase competitiveness by selling energy in the market that offers the best price, but also the additional flexibility allows the generator to participate in market-based arbitrage. This work will serve to fill that gap by developing a model that is inclusive of all four markets. In this work two frameworks are proposed that builds on the work developed in [10] and [11]. by developing one inclusive framework that considers all four markets.

Moreover, as the time gets closer to the actual time of participation, the accuracy of the information that the decision maker has increases. Stochastic programming models do not typically allow for information to be updated as it is made available. It goes without saying that having more accurate information can greatly impact the quality of the decisions made. Therefore, in this work, a second framework is developed that includes a mechanism to update scenarios and their associated probabilities through a phase-based approach. Thus, decisions are updated as more information becomes available to the decision maker.

4. Model Description

4.1. Short-term energy market structure

In this work, we will study the operation of a wind plant in a generalized energy market. The decision-making framework follows the temporal framework imposed by the energy market. To create the most generalized framework that is applicable to many markets, the framework studied in this work contains as many of the different forms of markets running concurrently and sequentially. We can think of the participation of W&SPP as split up between two main category of markets, the pool market (PM) and the reserve market, where the PM consists of the day-ahead, intra-day, and balancing market, as depicted in Figure 1. In this model we assume the generator assumes the role of a price-taker.
The generator must commit to how much it plans to buy/sell in each market. These commitments occur sequentially leading up to the time of actual participation as shown in Figure 2. The first commitments, and most important, are the commitments made in the morning of the day before in what is called the Day-Ahead market. This market typically yields the best return, however, at this point, information regarding availability of energy and market prices are inaccurate. At this point, the generator must also make commitments to reserve market regarding how much it will allocate to fulfill spot requirements made by the SO for regulation purposes. Later, starting from the evening of the day before the Intra-Day market is initiated wherein more accurate information regarding the market prices is available and the generator can adjust the commitments made. The generator is further able to adjust commitments throughout the next day in the Balancing Market.

4.2. Scenario dependent programming

Given the lack of accurate information at the time of decision making, i.e., the time that commitments of how much energy to buy/sell in each market for each hour are made, the problem is modeled using a stochastic programming approach. In this approach, decision variables are categorized into first stage, and second stage decisions. The first stage decisions are those that must be made ahead of time prior to accurate information being available. Second stage decisions are those that happen after information becomes available and are dependent on that information.
To model the uncertainty of the unknown parameters, scenarios are developed to come up with representative predictions of what the values could be, and probabilities are assigned to each of the scenarios. In this model, the unknown parameters are the available wind energy, market prices for all markets, and the regulation requirements. It is assumed that these parameters change on an hourly basis.

4.3. Stochastic programming frameworks

4.3.1. Single-phase framework

In this work we develop two frameworks. The first is a single-phase two-stage stochastic programming model and serves as a baseline. This model is the first in literature, as far as the author’s knowledge, to contain all the markets presented. All decisions made in D-1, which are the decisions associated with the participation of the W&SPP in DAM, IDM, and commitments to the RM, are considered as first stage variables as shown in Figure 4. Participation in the BM and actual participation in RM are modeled as scenario dependent second stage variables.
4.3.2. Multi-phase sequential framework

One major limitation to the baseline model is that if more information becomes available, and uncertain data becomes more accurate, we are unable to use that information to update decisions. As such a multi-phase model is developed where four two-stage stochastic programming models arranged sequentially as in Figure 5. This approach of allowing information to be updated and decisions to be revised early in the process is novel. Outputs (decisions) from one phase are fed into the following phase, and input (uncertain) data to the problem is used as soon as it becomes available or updated. In all problems the objective function is to maximize profit.

4.3.2.1. Phase 1

DAM Problem. The sequence begins with the problem of deciding how much to commit in the DAM. At this stage, the available wind energy and market prices are unknown and are represented by scenarios in the model. Potential participation in the other markets is represented in the model as second stage variables.

4.3.2.2. Phase 2

Regulation Band Problem. The reserve market is operated by the system operator (not the market operator as it is the case for DAM and IDM). The goal of this market is the regulation of real time power system operation. The system operator (SO) imposes a regulation band, and the agent must commit to provide a certain amount of power, which may be used by the SO in real time for regulation tasks in case it is needed. The fraction of the committed reserves that are required by SO for regulation tasks in real time is referred to as regulation requirements. The regulation band is a +/- amount of power that the generator may provide if required by the system operator. If the SO requires regulation up, it means that the generator is supposed to increase its generation. The converse applies for regulation down. This power market also runs under bidding mechanism and even though the system operator imposes the regulation, the system can still decide how much to participate and whether to fulfill the required commitments or incur a penalty.

In this work, it is supposed that just the ESS may be used for regulation requirements. It is challenging for a wind farm to perform regulation capabilities when available wind energy is uncertain. It is also needed to set the ratio between the regulations up and the total regulation band offered. This ratio must follow the ration assigned for the entire system. The parameter R is given by the system operator (in the Spanish case). It can be considered as a constant.

Note that regulation “up” refers to selling energy to the market, and “down” refers to buying energy.

4.3.2.3. Phase 3

IDM Problem. The intraday market has been shown to improving wind producers` competitiveness [34] when combined with the day ahead and balancing market [35], predominantly for its role in reducing balancing needs [36].

4.3.2.4. Phase 4

Real Time Problem. The real time problem involves the BM as well as real time energy offered for RM. During day D, for real time regulation purposes, the system operator may ask the generator to supply
regulation, i.e., a percentage of the regulation band committed. This percentage is modeled by the parameter $\pi$ which is considered uncertain.

![Diagram](image)

**Figure 5 – Overview of multi-phase framework**

Two frameworks will be presented in this work and the results will be compared. Framework A consists of one two-stage stochastic programming model in which all decisions are made at once. Framework B consists of four sequential two-stage stochastic programming models where decisions made at each of the first three steps are fed into sequential steps and are updated again in the final step.

Note, similar to the regulation market, balancing market price “up” refers to cost of buying energy, whereas “down” refers to price of selling energy.

The BM prices are defined as the imbalance prices from the source.

### 4.4. Nomenclature

| Sets and subindices | | | |
| --- | --- | --- | --- |
| $N_s$ | Number of scenarios under consideration |
| $T$ | Number of periods under consideration |
| $s$ | Subindex for scenarios, $s = 1, \ldots, N_s$ |
| $t$ | Subindex for time slots, $t = 1, \ldots, T$ |

| Parameters | | | |
| --- | --- | --- | --- |
| $\bar{P}_{\text{wind}}$ | Rated power of the wind farm (MW) |
| $E_{\text{ess}}^0$ | Initial energy stored in the ESS (MWh) |
| $\eta_{\text{in}}$ | Charging efficiency of the ESS |
| $\eta_{\text{out}}$ | Discharging efficiency of the ESS |
| $E_{\text{ess}}$ | Maximum energy stored in the ESS (MWh) |
| $P_{\text{ess}}$ | Maximum power to/from ESS (MW) |
| Symbol | Description |
|--------|-------------|
| $\text{SOC}^{\text{min}}$ | Minimum state of charge allowed for the ESS |
| $p_s$ | Probability of scenario $s$ |
| $\hat{P}^{\text{wind}}_{s,t}$ | Forecasted wind power available in every hour of scenario $s$ (MW) |
| $\hat{P}^{\text{prod}}_t$ | Amount of power generated in wind farm |

### Power Market Parameters

#### Energy Market

- $\beta_{s,t}^{\text{dam}}$: Scenario generated energy price in the DAM in every hour of day $D$ for scenario $s$ (€/MWh)
- $\beta_{s,t}^{\text{idm}}$: Scenario generated energy price in the IDM in every hour of day $D$ for scenario $s$ (€/MWh)
- $\lambda_{s,t}^{\text{bm,up}}$: Energy price of deviation up in every hour of day $D$ (€/MWh)
- $\lambda_{s,t}^{\text{bm,down}}$: Energy price of deviation down in every hour of day $D$ (€/MWh)

#### Reserve Market

- $R_{s,t}^{\text{rm,up}}$: Ratio between reserves up and total reserves. Constant.
- $k^{\text{rm}}$: Correction factor for cost of deviation in amount of every offered and required for regulation up and down in RM. Constant.
- $\gamma_{s,t}^{\text{rm,up}}$: Price of power reserve in every hour of day $D$ for scenario $s$ (€/MWh)
- $\beta_{s,t}^{\text{rm,up}}$: Price of energy under regulation up in RM for every hour of day $D$ (€/MWh)
- $\beta_{s,t}^{\text{rm,down}}$: Price of energy under regulation down in RM for every hour of day $D$ (€/MWh)
- $\lambda_{s,t}^{\text{rm,up}}$: Cost of deviation in amount of energy offered and required for regulation up in RM for every hour of day $D$ (€/MWh)
- $\lambda_{s,t}^{\text{rm,down}}$: Cost of deviation in amount of energy offered and required for regulation down in RM for every hour of day $D$ (€/MWh)
- $\pi_{s,t}^{\text{rm,up}}$: Regulation requirement up by SO in every hour of day $D$ for scenario $s$ (ratio between actual energy and reserved power)
- $\pi_{s,t}^{\text{rm,down}}$: Regulation requirement down by SO in every hour of day $D$ for scenario $s$ (ratio between actual energy and reserved power)
- $k^{\text{rm}}$: Correction factor of deviation prices in RM

### Decision variables

#### Overall System

- $p^{\text{wind}}_{s,t}$: Amount of power produced by the wind farm (MW)
- IDAM: Total income from participation in the day-ahead market for day $D$
- IDM: Total income from participation in the intraday market for day $D$
- IBM: Total income from participation in the balancing market for day $D$
- IRM: Total income from participation in the reserve market for day $D$

#### ESS Operation

- $E_{s,t}^{\text{ess}}$: Energy stored in the ESS in every hour of day $D$ (MWh)
- $P_{s,t}^{\text{ess,in}}$: Power entering to the ESS in every hour of day $D$ (MW)
- $P_{s,t}^{\text{ess,out}}$: Power delivered by the ESS in every hour of day $D$ (MW)
- $\text{SOC}_{s,t}^{\text{ess}}$: State of charge of ESS in every hour of day $D$ for scenario $s$

#### Energy Market

- $\beta_{t}^{\text{dam}}$: Final power committed in the DAM for every hour of day $D$ (MW)
- $\beta_{t}^{\text{idm}}$: Final power committed in the IDM in every hour of day $D$ (MW)
**4.5. Framework A**

Framework A consists of a two-stage stochastic programming model in which the objective is to maximize the income of the operation of the system participating in all markets considered: DAM, IDM, BM, and RM.

4.5.1. Objective Function of Framework A

The objective function of Framework A is to maximize the cumulative income from the four markets, the day-ahead market, intra-day market, balancing market, and reserve market.

\[
\text{maximize (IDAM + IIDM + IBM + IRM)} \tag{1}
\]

\[
\text{IDAM} = \sum_{s=1}^{N_s} \rho_s \left( \sum_{t} \beta_{s,t}^\text{dam} \hat{P}_{t}^\text{dam} \right) \tag{2}
\]

\[
\text{IRM} = \sum_{s=1}^{N_s} \rho_s \left( \sum_{t} \gamma_{s,t}^\text{rm} \hat{P}_{t}^\text{rm} + \sum_{t} \beta_{t}^\text{rm,up} E_{s,t}^\text{rm,up} - \sum_{t} \beta_{t}^\text{rm,dw} E_{s,t}^\text{rm,dw} - \sum_{t} \lambda_{t}^\text{rm,up} D_{s,t}^\text{rm,up} \right. \\
\left. - \sum_{t} \lambda_{t}^\text{rm,dw} D_{s,t}^\text{rm,dw} \right) \tag{3}
\]

\[
\text{IIDM} = \sum_{s=1}^{N_s} \rho_s \left( \sum_{t} \beta_{s,t}^\text{idm} \hat{P}_{t}^\text{idm} \right) \tag{4}
\]

\[
\text{IBM} = \sum_{s=1}^{N_s} \rho_s \left( \sum_{t} \lambda_{s,t}^\text{bm,up} \Delta_{s,t}^\text{bm,up} - \sum_{t} \lambda_{s,t}^\text{bm,dw} \Delta_{s,t}^\text{bm,dw} \right) \tag{5}
\]
\[
\text{maximize} \sum_{s=1}^{N_s} \rho_s \left( \sum_t \beta_{s,t}^{dam} \hat{P}_t^{dam} + \sum_t \beta_{s,t}^{dm} \hat{P}_t^{dm} + \sum_t \gamma_{s,t}^{rm} \hat{P}_t^{rm} + \sum_t \beta_t^{rm,up} \hat{P}_t^{rm,up} \right.
\]
\[
- \sum_t \beta_t^{rm,down} E_t^{rm,down} - \sum_t \lambda_t^{rm,up} D_t^{rm,up} - \sum_t \lambda_t^{rm,down} D_t^{rm,down} \\
+ \sum_t \gamma_{s,t}^{bm,up} \Delta_{s,t}^{bm,up} - \sum_t \lambda_{s,t}^{bm,down} \Delta_{s,t}^{bm,down} \right)
\]

The income equation for the RM (3) is a combination of the income from the amount of energy committed towards the RM \((\sum_t \gamma_{s,t}^{rm} \hat{P}_t^{rm})\), income from energy actually offered for reg up in RM \((\sum_t \beta_t^{rm,up} \hat{P}_t^{rm,up} - \sum_t \beta_t^{rm,down} E_t^{rm,down})\), and costs associated with deviating from requirements \((\sum_t \lambda_t^{rm,up} D_t^{rm,up} - \sum_t \lambda_t^{rm,down} D_t^{rm,down})\).

4.5.2. Constraints of Framework A

Operation of W&SPP:

The available wind energy could be more than rated power of farm, however, the maximum amount of power that can be produced is capped at the rated power of the farm.

\[
P_{s,t}^{wind} \leq \hat{P}_{s,t}^{wind} \quad \forall t \in T, \forall s \in S \quad (7)
\]
\[
P_{s,t}^{wind} \leq \bar{P}_{s,t}^{wind} \quad \forall t \in T, \forall s \in S \quad (8)
\]

These constraints are the same as in the frameworks presented in ref [11] and ref [10]. These constraints will also be the same for every phase of every framework presented in this work. Henceforth in this work, Operation of W&SPP Constraints will refer to equations (9)-(15).

Constraint (9) defines the amount of energy stored in ESS in every time step as a function of the initial conditions, power entering and leaving the ESS, and the efficiency of the charging and discharging processes.

\[
E_{s,t}^{ess} = E_{s,t}^{ess,initial} + \sum_{\tau=1}^{t} \eta_{in} p_{s,t}^{ess,in} - \sum_{\tau=1}^{t} \frac{1}{\eta_{out}} p_{s,t}^{ess,out} \quad \forall t \in T
\]  

Constraints (10)-(12) limit the maximum and minimum energy stored in the ESS.

\[
E_{t}^{ess} \leq \bar{E}_{s,t}^{ess} \quad \forall t \in T \quad (10)
\]
\[
SOC_{s,t} = E_{s,t}^{ess} / \bar{E}_{s,t}^{ess} \quad \forall t \in T, \forall s \in S \quad (11)
\]
\[
SOC_{s,t} \geq \text{SOC}_{s,t}^{\text{min}} \quad \forall t \in T, \forall s \in S \quad (12)
\]

Constraints (17)-(18) limit the maximum power that can be exchanged by ESS at any time.
\[ p_{s,t}^{\text{ess, out}} \leq \bar{p}_{\text{ess}} \quad \forall t \in T, \forall s \in S \]  
\[ p_{s,t}^{\text{ess, in}} \leq \bar{p}_{\text{ess}} \quad \forall t \in T, \forall s \in S \]  

Constraint (16) is non-negative restrictions.

\[ p_{s,t}^{\text{ess, out}}, p_{s,t}^{\text{ess, in}}; E_{s,t}^{\text{ess}} \geq 0 \quad \forall t \in T, \forall s \in S \]  

Constraints for EM

The EM is a combination of the DAM and IDM, as in constraint (18). Constraint (16) limits the maximum power that can be bought/sold in the DAM. Lower bound is constrained by how much ESS can store, maximum bound is the capacity of the wind farm plus whatever the ESS is able to give. Similarly, constraint (17) limits the maximum power that can be bought/sold in the IDM.

\[ -\bar{p}_{\text{ess}} \leq \hat{p}_{\text{dam}} \leq p_{\text{wind}} + \bar{p}_{\text{ess}} \quad \forall t \in T \]  
\[ |\hat{p}_{\text{dam}}| \leq p_{\text{wind}} + \bar{p}_{\text{ess}} \quad \forall t \in T \]  
\[ \hat{p}_{\text{t}}^{\text{pm}} = \hat{p}_{\text{dam}} + \hat{p}_{\text{t}} \quad \forall t \in T \]  

Deviations in the EM are covered by the BM as in constraints (21)-(23).

\[ \Delta_{s,t}^{bm} = \hat{p}_{s,t}^{bm} - \hat{p}_{s,t} \quad \forall t \in T, \forall s \in S \]  
\[ \Delta_{s,t}^{bm, up} = \hat{p}_{s,t}^{bm, up} - \hat{p}_{s,t} \quad \forall t \in T, \forall s \in S \]  
\[ \hat{p}_{s,t}^{bm, up} \leq p_{\text{wind}} + \bar{p}_{\text{ess}} \quad \forall t \in T \]  
\[ \hat{p}_{s,t}^{bm, dw} \leq p_{\text{wind}} + \bar{p}_{\text{ess}} \quad \forall t \in T \]  
\[ \hat{p}_{s,t}^{bm, up}, \hat{p}_{s,t}^{bm, dw} \geq 0 \quad \forall t \in T, \forall s \in S \]  

Constraints for the Reserve Market:

In this work we model the penalty for not fulfilling reserve market requirements by defining a parameter \( \kappa^{rm} > 1 \) and including the set of equations (24) and (25).

\[ \lambda_{s,t}^{rm, up} = \kappa^{rm} \beta_{s,t}^{rm, up} \quad \forall t \in T, \forall s \in S \]  
\[ \lambda_{s,t}^{rm, dw} = \kappa^{rm} \beta_{s,t}^{rm, dw} \quad \forall t \in T, \forall s \in S \]  

Constraints define the regulation band that can be offered by the W&SPP.

\[ \hat{p}_{t}^{rm} = \hat{p}_{t}^{rm, up} + \hat{p}_{t}^{rm, dw} \quad \forall t \in T \]  
\[ \hat{p}_{t}^{rm, up} \leq \bar{p}_{\text{ess}} \quad \forall t \in T \]  
\[ \hat{p}_{t}^{rm, dw} \leq \bar{p}_{\text{ess}} \quad \forall t \in T \]  

Defines ratio assigned for entire system. This is a ratio given as a constant by the SO.

In some markets they are asymmetric, and they do not care about the shape. But in the Spanish market, there is this constraint. They fix the rate based on the general requirement of the system.

\[ \hat{p}_{t}^{rm, up} / \hat{p}_{t}^{rm} = R^{rm, up} \quad \forall t \in T \]
Set amount of energy required by SO for regulation tasks.

\[
\tilde{E}_{s,t}^{rm,up} = \pi_{s,t}^{rm,up} \cdot \tilde{p}_{t}^{rm,up} \quad \forall t \in T, \forall s \in S
\]

\[
\tilde{p}_{s,t}^{rm,down} = \pi_{s,t}^{rm,down} \cdot \tilde{p}_{t}^{rm,down} \quad \forall t \in T, \forall s \in S
\]

Actual energy supplied by W&SPP for regulation tasks

\[
E_{s,t}^{rm,up} \leq \tilde{E}_{s,t}^{rm,up} \quad \forall t \in T, \forall s \in S
\]

\[
E_{s,t}^{rm,down} \leq \tilde{E}_{s,t}^{rm,down} \quad \forall t \in T, \forall s \in S
\]

Define deviations in the RM

\[
D_{s,t}^{rm,up} = E_{s,t}^{rm,up} - \tilde{E}_{s,t}^{rm,up} \quad \forall t \in T, \forall s \in S
\]

\[
D_{s,t}^{rm,down} = E_{s,t}^{rm,down} - \tilde{E}_{s,t}^{rm,down} \quad \forall t \in T, \forall s \in S
\]

Non-negativity constraints

\[
\tilde{p}_{t}^{rm,up}, \tilde{p}_{t}^{rm,down}, \tilde{E}_{s,t}^{rm,up}, \tilde{E}_{s,t}^{rm,down} \geq 0 \quad \forall t \in T, \forall s \in S
\]

Power balance for all markets

Commitments acquired in day D-1

\[
P_{s,t} = p_{t}^{wind} + p_{t}^{ess, out} - p_{t}^{ess, in} \quad \forall t \in T, \forall s \in S
\]

\[
P_{s,t} = p_{s,t}^{pm} + \tilde{E}_{s,t}^{rm,up} - \tilde{E}_{s,t}^{rm,down} \quad \forall t \in T, \forall s \in S
\]

This concludes Framework A. In the following section, Framework B is given.

### 4.6. Framework B: Four sequential phases

Framework B consists of four sequential two-stage stochastic programming models that feed into one another. Phase one is the DAM problem, phase two is the RM problem, phase three is the IDM problem, and phase four is the real time problem. After each phase is solved, the results are fed into the subsequent problem.

One way of summarizing Framework B is by looking at which variables are scenario dependent, scenario independent, and which variables become fixed parameters in the following phase.

Note: as with Framework A, we assume deviations in DAM and IDM are covered in the BM.
Decision Variables

| Phase 1: (Unknown market prices, Unknown AWE) | Fixed from previous phase | Scenario Independent | Scenario Dependent |
|---------------------------------------------|---------------------------|----------------------|-------------------|
| Phase 2: (DAM prices known, other market prices unknown, Updated AWE) | $\beta_t^{dam}$ | $\beta_t^{rm}$ | $\Delta_{s,t}^{bm}$, $E_{s,t}^{rm}$, $D_{s,t}^{rm}$ |
| Phase 3: (DAM prices known, RM price known, other market prices unknown, Updated AWE) | $\beta_t^{dam}$, $\beta_t^{idm}$ | $\beta_t^{rm}$ | $\Delta_{s,t}^{bm}$, $E_{s,t}^{rm}$, $D_{s,t}^{rm}$ |
| Phase 4: (All market prices known, Updated AWE forecasts) | $\beta_t^{dam}$, $\beta_t^{idm}$, $\beta_t^{rm}$ | - | $\Delta_{s,t}^{bm}$, $E_{s,t}^{rm}$, $D_{s,t}^{rm}$ |

Table 1: Scenario-dependent and scenario independent variables for Multi-phase model

4.6.1. Phase 1 of Framework B

Phase 1 is the DAM problem.

1\textsuperscript{st} stage variables: commitments made in DAM in day D-1

2\textsuperscript{nd} stage variables: participation in RM, IDM, BM, ESS operation.

Note, at this stage all prices are unknown, and forecasts are inaccurate.

$$\text{maximize } (\text{IDAM} + \text{I IDM} + \text{IBM} + \text{IRM})$$

$$\text{IDAM} = \sum_s \rho_s \left( \sum_t \beta_t^{dam} \beta_t^{dam} \right)$$

$$\text{IRM} = \sum_{s=1}^{N_s} \rho_s \left( \sum_t \gamma_t^{rm,up} \beta_t^{rm,up} + \sum_t \beta_t^{rm,up} E_t^{rm,up} - \sum_t \beta_t^{rm,up} E_t^{rm,up} - \sum_t \lambda_t^{rm,up} D_t^{rm,up} - \sum_t \gamma_t^{rm,up} D_t^{rm,up} \right)$$

$$\text{I IDM} = \sum_{s=1}^{N_s} \rho_s \left( \sum_t \beta_t^{idm} \beta_t^{idm} \right)$$

$$\text{IBM} = \sum_{s=1}^{N_s} \rho_s \left( \sum_t \lambda_t^{bm,up} \Delta_t^{bm,up} + \sum_t \lambda_t^{bm,up} \Delta_t^{bm,up} - \sum_t \lambda_t^{bm,up} \Delta_t^{bm,up} \right)$$

$$\text{maximize } \sum_{s=1}^{N_s} \rho_s \left( \sum_t \beta_t^{dam} \beta_t^{dam} + \sum_t \gamma_t^{rm} \beta_t^{rm} + \sum_t \beta_t^{rm,up} E_t^{rm,up} - \sum_t \beta_t^{rm,up} E_t^{rm,up} - \sum_t \lambda_t^{rm,up} D_t^{rm,up} - \sum_t \lambda_t^{rm,up} D_t^{rm,up} \right)$$

$$\text{maximize } \sum_{s=1}^{N_s} \rho_s \left( \sum_t \beta_t^{idm} \beta_t^{idm} + \sum_t \lambda_t^{bm,up} \Delta_t^{bm,up} + \sum_t \lambda_t^{bm,up} \Delta_t^{bm,up} \right)$$
Constraints:

W&SPP Operational Constraints as in Framework A given by equations (11)-(20).

4.6.2. Phase 2 of Framework B

RM Problem. At this point decisions have already been made as to how much the system will commit to the DAM, and there is new information regarding the requirements made by the system operator. AWE forecast is updated. DAM prices are known.

Again, the objective is to maximize total income.

Decisions regarding DAM have already been made and will not be modified during this phase.

1\textsuperscript{st} stage variables: commitments to RM made in day D-1

2\textsuperscript{nd} stage variables: participation in IDM, BM, ESS operation and deviations in participation in RM.

\begin{align*}
\text{maximize } & (\text{IIDM } + \text{IBM } + \text{IRM}) \\
\text{IRM} = & \sum_{s=1}^{N_s} \rho_s \left( \sum_t \gamma_{s,t} r_{rm,t} + \sum_t \beta_{t}^{rm,up} E_{s,t}^{rm,up} - \sum_t \beta_{t}^{rm,down} E_{s,t}^{rm,down} - \sum_t \lambda_{t}^{rm,up} D_{s,t}^{rm,up} \right) \\
\text{IIDM} = & \sum_{s=1}^{N_s} \rho_s \left( \sum_t \beta_{s,t}^{idm} f_{s,t}^{idm} \right) \\
\text{IBM} = & \sum_{s=1}^{N_s} \rho_s \left( \sum_t \lambda_{s,t}^{bm,up} A_{s,t}^{bm,up} - \sum_t \lambda_{s,t}^{bm,down} A_{s,t}^{bm,down} \right) \\
\text{maximize } & \sum_{s=1}^{N_s} \rho_s \left( \sum_t \gamma_{s,t} r_{rm,t} + \sum_t \beta_{t}^{rm,up} E_{s,t}^{rm,up} - \sum_t \beta_{t}^{rm,down} E_{s,t}^{rm,down} - \sum_t \lambda_{t}^{rm,up} D_{s,t}^{rm,up} \right) \\
& - \sum_t \lambda_{t}^{rm,down} D_{s,t}^{rm,down} + \sum_t \beta_{s,t}^{idm} f_{s,t}^{idm} + \sum_t \lambda_{s,t}^{bm,up} A_{s,t}^{bm,up} \\
& - \sum_t \lambda_{s,t}^{bm,down} A_{s,t}^{bm,down} \right)
\end{align*}

Constraints:

W&SPP Operational Constraints given by equations (11)-(20).
4.6.3. Phase 3 of Framework B

IDM Problem

Decisions regarding DAM and RM have already been made and will not be modified here.

1st stage variables: commitments to IDM made in day D-1

2nd stage variables: participation in BM, ESS operation and deviations in participation in IDM.

\[
\begin{align*}
\text{maximize } & (\text{IIDM} + \text{IBM} + \text{IRM}) \\
\text{IRM} & = \sum_{s=1}^{N_s} \rho_s \left( \sum_t \beta_{t, \text{rm,up}}^{\text{rm,up}} E_{s,t}^{\text{rm,up}} - \sum_t \beta_{t, \text{rm,dw}}^{\text{rm,dw}} E_{s,t}^{\text{rm,dw}} - \sum_t \lambda_t^{\text{rm,up}} D_{s,t}^{\text{rm,up}} ight) \\
\text{IIDM} & = \sum_{s=1}^{N_s} \rho_s \left( \sum_t \beta_{t, \text{idm}}^{\text{idm}} \hat{P}_{t, \text{idm}} \right) \\
\text{IBM} & = \sum_{s=1}^{N_s} \rho_s \left( \sum_t \lambda_s^{\text{bm,up}} B_{s,t}^{\text{bm,up}} - \sum_t \lambda_s^{\text{bm,dw}} \Delta_{s,t}^{\text{bm,dw}} \right)
\end{align*}
\]

Constraints:

W&SPP Operational Constraints given by equations (11)-(20).

4.6.4. Phase 4 of Framework B

Real time problem – note, there are no scenario-independent variables.

\[
\begin{align*}
\text{maximize } & (\text{IBM} + \text{IRM}) \\
\text{IRM} & = \sum_{s=1}^{N_s} \rho_s \left( \sum_t \beta_{t, \text{rm,up}}^{\text{rm,up}} E_{s,t}^{\text{rm,up}} - \sum_t \beta_{t, \text{rm,dw}}^{\text{rm,dw}} E_{s,t}^{\text{rm,dw}} - \sum_t \lambda_t^{\text{rm,up}} D_{s,t}^{\text{rm,up}} ight) \\
\text{IBM} & = \sum_{s=1}^{N_s} \rho_s \left( \sum_t \lambda_s^{\text{bm,up}} B_{s,t}^{\text{bm,up}} - \sum_t \lambda_s^{\text{bm,dw}} \Delta_{s,t}^{\text{bm,dw}} \right)
\end{align*}
\]
\[
\max \sum_{s=1}^{N_s} \rho_s \left( \sum_t \beta_t^{rm,up} E_{s,t}^{rm,up} - \sum_t \beta_t^{rm,down} E_{s,t}^{rm,down} - \sum_t \lambda_t^{rm,up} D_{s,t}^{rm,up} \right. \\
\left. - \sum_t \lambda_t^{rm,down} D_{s,t}^{rm,down} + \sum_t \lambda_s^{bm,up} \Delta_{s,t}^{bm,up} - \sum_t \lambda_s^{bm,down} \Delta_{s,t}^{bm,down} \right) 
\] (58)

Constraints:

W&SPP Operational Constraints given by equations (11)-(20).

This concludes Framework B. In the following section the simulation procedure is described, and some results are shared along with some insights from the results.

5. Simulation and results

The goal of this section is to describe and evaluate the two proposed frameworks. To do this we run a simulation of a length of 60 days starting from a random day within a 1-year dataset of prices, wind energy, and regulation requirements from a Spanish energy market.

Scenarios are generated for each of the three unknown parameters – available wind energy, price, and regulation requirements, using different methodologies and are of different sizes for each in order to demonstrate the framework’s capabilities of handling different types of scenarios. The scenarios are fed into the model and the model produces theoretical expected net income given the optimal decisions generated. In order to evaluate the quality of the decisions generated, the decisions generated are fed into a deterministic model and the results are compared.

In the following sections, the scenarios and their generation methods are described, followed by some results and key insights.

5.1. Scenario generation to handle uncertainty

Stochastic programming was selected for this work due to the uncertainty associated with the values of certain parameters when decision making takes place a day ahead of actual participation of a wind farm in the energy market. Stochastic programming allows for the inclusion of a set of scenarios that aim to represent the possible values of the parameters with a certain probability.

There is a myriad of scenario generation approaches that are used in combination with stochastic programming. In references [10], [11] various scenario generation approaches are implemented and compared. In this work, we select three different approaches explored in [10], [11] for each of the parameters. Different approaches are used for each of the parameters to demonstrate the flexibility of the model. For simplicity, it is assumed that each of the unknown parameters are independent of one another.

Total number of scenarios is a product of the number of available wind energy scenarios, the number of different market prices scenarios, and the number of regulation requirement scenarios. In this work, we will see in the following sections that the scenario tree contains \(3 \times 10 \times 3 = 90\) scenarios.
5.1.1. Wind Energy Scenarios

To forecast amount of energy produced by the wind farm, we need to have forecasts of the available wind energy. Probabilistic forecast for available wind energy in day D is provided by the wind farm operator as a set of time series on a percentile basis. Each time series corresponds to a set of hourly values defining an upper bound on the actual available wind energy with a given probability. Three scenarios are generated from curves p75, p50 and, p25.

![Available Wind Energy Scenarios from Probabilistic Forecasting](image)

*Figure 6 Scenarios of available wind energy from probabilistic forecasts*

Multiple forecasts are made available in day D – 1 for day D, becoming more accurate as it become closer to day D. This is particularly helpful for Framework B, where for each phase the energy forecast is updated.

5.1.2. Market Price Scenarios

For market prices, we combine in one scenario a full day of data for each market, therefore one scenario comprises of 24 hours x 7 market prices = 168 attributes. We do this by taking 1 year’s data, and arranging them into 365 vectors, where each vector is 1 day with 168 attributes, then applying a k-means algorithm to separate them into 10 clusters. The centroid of each cluster is used as scenarios, and probabilities are assigned to the scenarios using frequentist reasoning, i.e., with the probability of each scenario set to equate the number of vectors assigned to each cluster as a ratio to the total number of vectors.

5.1.3. Regulation Requirement Scenarios

The k-means algorithm is also used for the regulation requirements, but we take a simpler approach where each data point contains two attributes, regulation up and regulation down, and is then separated into 3 clusters. Again, the scenarios are set to be the centroids of each cluster, and the probability of the occurrence of each scenario is based on the number of observations that fall in each cluster.

5.2. Daily operation decision analysis Framework comparison
The operational decisions for one day D are presented in Figure 7. The actual available wind energy and market prices for a given day are shown in the two upper sub figures. The third and fourth subfigures represent the participations of the wind farm in the various markets given the decisions that are produced using framework’s A and B, respectively.
Since the penalty for overgeneration is less than the spot market price, the producer commits to the maximum amount that it can and makes up for any shortfalls by buying in the other markets. This is regardless of the wind forecast.

An interesting point is that for both frameworks, the wind farm prioritizes selling in the DAM even at a cost of purchasing energy from the IDM to make up for the production deficiency due to unavailable wind energy. It does so to the extent that the farm sells the maximum allowable energy it can, which is capped at the rated power of the wind farm. We see that in framework B, this strategy is taken further in that the maximum allowable energy that can be bought in the IDM is bought, and the excess is all sold in the BM.

If we compare the results of net income for a set of 60 days starting from a random day within our dataset, we see that Framework B clearly performs better than Framework A as shown in Figure 8. The mean expected net income increases by 4387.55 Euro, 51% when running the same data through framework A to framework B.
If we compare the net income from Framework B for each phase, we see that the result improves with each consecutive phase as shown in Figure 6. This follows intuition since with each phase the information is updated, thus there is a lower likelihood of paying penalties due to poor forecasting.

6. Conclusion

The work presented is aimed at expanding upon frameworks created to optimize the participation of wind energy producers in multiple energy markets. It did so by developing two frameworks using stochastic optimization models. The first consisted of a single model in which decisions regarding four different markets that operate in varying ways were made at one moment while accounting for unknown parameters through scenarios that are assigned probabilities. The second framework consisted of four stochastic optimization models, where first-stage decisions made in one model fed into successive models, and scenarios were updated as more information became available to the decision-maker.

These frameworks demonstrated the increased economic benefit of allowing the energy producer to participate in all the markets. In every one of the runs, the participation of the wind energy producer in each one of the markets was significant to the strategy, decisions made, and overall profit.

The comparison between the two frameworks demonstrated the importance of updated information as forecasts become more accurate when the time comes closer to that of actual participation. In the experiment that we ran, we saw a mean of 51% improvement in the profitability of the farm in the second framework where the forecasts were updated compared to the first framework. The model aids in better decision making, addresses uncertainty related to variable resource generators and optimizes the return on investment. However, the better results also came at a cost of increased computational effort.

There are several limitations for these frameworks that could be opportunities for further work. Firstly, in stochastic programming, scenarios are mutually exclusive of each other. In reality, the unknown parameters could be dependent, such as market prices being driven by supply and demand, which are influenced by the availability of energy. Thus, in a place that has high utilization of wind energy, the availability of wind will have an impact on the availability of energy, and thus, the market prices. Secondly, in this work, the producer is assumed to be a price taker. The price taker model cannot model the price interaction between the generation offer and the market clearing price. If the producer is large enough, bids could influence the market.
To further improve the model, the energy storage system could be considered as a second stage variable for added flexibility, however, this greatly increases the computational time of the model. Another opportunity for improvement would be to perform a case study on forecasting methods of wind power, regulation reserve, and prices data, and apply the different methods to the frameworks presented. Lastly, the proposed models do not factor in the amount of risk associated with the proposed solution. Future work could quantify and minimize the risk of the solution offered.
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