



Payment mechanisms for electricity markets with uncertain supply

Ryan Cory-Wright^{a,*}, Andy Philpott^b, Golbon Zakeri^b

^a Operations Research Center, Massachusetts Institute of Technology, United States

^b Electric Power Optimization Centre, The University of Auckland, New Zealand

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ABSTRACT

This paper provides a framework for deriving payment mechanisms for intermittent, flexible and inflexible electricity generators who are dispatched according to the optimal solution of a stochastic program that minimizes the expected cost of generation plus deviation. The first stage corresponds to a pre-commitment decision, and the second stage corresponds to real-time generation that adapts to different realizations of a random variable. By taking the Lagrangian and decoupling in different ways we study two payment mechanisms with different properties.

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1. Introduction

In response to pressure to reduce CO₂ emissions and increases in the penetration of renewables, electricity pool markets are procuring increasing amounts of electricity from intermittent sources such as wind and solar. This pressure can cause difficulties for the independent system operator (ISO) when dispatching generators. These difficulties arise because many thermal generators are inflexible and need to be informed of their generation obligations before the output of renewables is known.

In markets with large amounts of inflexible generation, generators can be provided with a pre-commitment setpoint before the generation output of renewables is known. The setpoint is determined by assuming that renewables generate their expected output capacity. The ISO then dispatches generators at the commencement of the trade period, with the objective of minimizing the cost of generation plus deviation from the setpoint, in order to manage fluctuations between the expected and the realized output capacity of intermittent renewables. We refer to this dispatch mechanism as the traditional mechanism.

As noted by Chao et al. in [3] this approach can be suboptimal in maximizing consumer welfare. The expected costs of corrective actions arising from surpluses or shortfalls are not priced into the market clearing problem, because the system operator does not consider uncertainty. Dispatches derived via the traditional mechanism therefore may have a small fuel cost and a large expected cost of correction.

With small quantities of intermittent renewable penetration the price of failing to consider uncertainty is small, as flexible

generators can be re-dispatched at a low cost to meet shortfalls. However, as intermittent renewables increase their penetration, the cost of corrective actions becomes significant. Limits on flexible plants mean that expensive and inflexible plants need to be re-dispatched to meet large shortfalls in wind or solar generation. Therefore, when the penetration of intermittent renewables is high, a new dispatch mechanism is required.

The first alternative to the traditional dispatch mechanism was proposed by Bouffard and Galiana in [2], which involves clearing a co-optimized pool and reserve market using a two-stage stochastic program. The first stage is a capacity market which is cleared before random events pertaining to the availability of plants and transmission lines take on a realization. The second stage is a market clearing problem where only units committed in the first stage may be dispatched.

Subsequently, several authors including [9,7,4,5,10] have proposed explicitly modelling uncertainty in the generation output of intermittent renewables as a random variable. Existing ancillary market services are supplemented with a real-time market, which is cleared after the generation capacity of renewables is realized. This can be achieved by casting the market clearing problem within a two-stage stochastic programming framework, where the first stage corresponds to a pre-commitment setpoint, and the second stage corresponds to a real-time dispatch under a particular realization of the generation output of renewables. We refer to this dispatch mechanism as the *Stochastic Dispatch Mechanism*, or SDM.

In SDM, the pre-commitment setpoint can be interpreted as the output level at which generators prepare to generate before wind generation is realized. The real-time dispatch quantity is the generation quantity which the generator produces throughout the trade period, after the generation of renewables is known. A deviation to increase or decrease a generators real-time dispatch

* Corresponding author.

E-mail address: ryancw@mit.edu (R. Cory-Wright).

output from its day-ahead setpoint causes the generator to incur a cost, in the form of e.g. wear-and-tear on generation equipment.

To replicate the dispatch found by SDM and maximize expected total social welfare, it is necessary to pay market participants in a manner which causes their optimal behaviour to align with the optimal dispatch found by a system operator when solving SDM. In the literature (see [9,7,4,10]) this is achieved by compensating and charging market participants with a single-settlement payment mechanism, where the amount charged to each participant under each possible realization of renewable generation is made known apriori, and the actual charge to each participant occurs after renewable generation is realized.

In single-settlement payment mechanisms, two desirable attributes are revenue adequacy and cost recovery. A payment mechanism is revenue adequate if and only if the system operator collects at least as much from consumers as it pays generators. A payment mechanism exhibits cost recovery if and only if generators are paid at least as much as their fuel costs.

The first paper to study this aspect of pricing was by Wong and Fuller [9] who introduced a two-stage dispatch mechanism and suggested several payment mechanisms to compensate generators that were revenue adequate and recovered costs on average. A similar approach was taken by Pritchard et al. [7] who focused on wind intermittency. The dispatch mechanism of [7] was improved by Zakeri et al. in [10], who observed that welfare could be enhanced by removing the first-stage constraint on supply meeting demand, and suggested an alternative payment mechanism, which is revenue adequate in every scenario and provides generator cost recovery on average.

In this paper, we revisit the dispatch mechanism of [10] in a classical Lagrangian framework for modelling perfectly competitive partial equilibrium. We define a price of information, the amount which a generator needs to be paid to enforce nonanticipativity on its first-stage generation. The price of information leads to a discriminatory variation on the pricing mechanism of [10], giving cost recovery in every scenario, expected revenue adequacy and expected revenue equivalence for all agents compared to [10]'s mechanism, assuming that agents behave in the risk-neutral price-taking manner assumed in [7] and [10]. This discriminatory variation explicitly identifies the uplift payment required to make all generators whole, and ensures that the expected uplift payment to each generator is zero.

2. The stochastic dispatch mechanism

Following [7] and [10], we consider a SDM based on the DC-Load Flow model of a constrained electricity transmission network. We follow [1] in letting uncertainty be represented by the scenario $\omega \in \Omega$, which occurs with probability $P(\omega)$. We assume that a realization of ω prescribes all uncertainty due to intermittent generation in an electricity pool market, and that the sample space Ω is a finite set containing all possible future realizations of ω . Although the real distribution of wind is not finite, Ω can be viewed as an approximation, obtained for example by sampling from the true distribution if this is available. The dispatch models obtained are then Sample Average Approximations for which one can derive asymptotic convergence results as the sample size increases (see [8] for a general theory, and [10] for asymptotic results in the context of SDM). We note that any computational dispatch model must work with a finite Ω , and since our focus in this paper is on different payment mechanisms for these models, we restrict attention to this case.

Our notation closely follows that of [7] and [10] in which deterministic variables are denoted by lower case Roman symbols, random variables by upper case Roman symbols, and prices by lower case Greek symbols.

The sets and indices in the Stochastic Program (SP) solved to obtain the day-ahead setpoint in SDM are defined as follows:

- i is the index of a generator. We assume perfect competition, so the ownership of generation does not affect the solution. This means that each agent i can be thought of as operating a single unit i .
- \mathcal{N} is the set of all nodes in the transmission network.
- $j(i)$ is the node $j \in \mathcal{N}$ where generator i is located.
- $a_{in} = 1$ when agent i is located at node n and 0 otherwise.
- $\mathcal{T}(n)$ is the set of all offers at node n .
- \mathcal{F} is a set constraining the flows in the network to meet thermal limits and the DC-Load Flow constraints imposed by Kirchhoff's Laws. We assume that $0 \in \mathcal{F}$.

The decision variables in SP are defined as follows:

- x_i is the day-ahead setpoint level which generator i is advised to prepare to produce before the generation capacity of intermittent renewables is known.
- $X_i(\omega)$ is the real-time dispatch produced by generator i in scenario ω .
- $U_i(\omega)$ and $V_i(\omega)$ are the amounts which generator i deviates up/down by in scenario ω . That is, $U_i(\omega) = \max(X_i(\omega) - x_i, 0)$, and $V_i(\omega) = \max(x_i - X_i(\omega), 0)$.
- $F(\omega) \in \mathcal{F}$ is the vector of branch flows in the network in scenario ω .
- $\tau_n(F(\omega))$ is the net amount of energy flowing from the grid into node n in scenario ω . We assume that τ_n is a concave function of F with $\tau_n(0) = 0$, $\forall n \in \mathcal{N}$.

The shadow prices for the constraints in SP are defined as follows:

- $\lambda_n(\omega)$ is the marginal cost of generating one additional unit of electricity at node n in scenario ω under SP. As the constraint on supply meeting demand is an inequality, we require that $\lambda_n(\omega) \geq 0$, $\forall n \in \mathcal{N}$.
- $\rho_i(\omega)$ is the marginal cost of agent i generating one additional unit of electricity in scenario ω under SP.
- $\bar{\lambda}_n = \mathbb{E}_\omega[\lambda_n(\omega)]$ is the expected value of the shadow price $\lambda_n(\omega)$ in SP.

The problem data in SP are defined as follows:

- c_i is the marginal cost incurred by generator i .
- $D_n(\omega)$ is the consumer demand at node n in scenario ω .
- $r_{u,i}$ and $r_{v,i}$ are the marginal costs incurred by generator i for deviating up or down in its generation. We require that $r_{u,i} > c_i > r_{v,i}$ to avoid providing generator i with arbitrage opportunities when it is choosing whether to ramp up or down.
- $G_i(\omega)$ is the maximum output capacity of generator i in scenario ω .

The day-ahead setpoint is found by solving the following stochastic program for x , as defined by Zakeri et al. in [10]:

$$\begin{aligned} \text{SP: } \min & c^\top x + \sum_{\omega} P(\omega)(r_u^\top U(\omega) + r_v^\top V(\omega)) \\ \text{s.t. } & \sum_{i \in \mathcal{T}(n)} X_i(\omega) + \tau_n(F(\omega)) \geq D_n(\omega), \forall n, \forall \omega \in \Omega, [P(\omega)\lambda_n(\omega)], \\ & x + U(\omega) - V(\omega) = X(\omega), \forall \omega \in \Omega, [P(\omega)\rho(\omega)], \\ & F(\omega) \in \mathcal{F}, \forall \omega \in \Omega, \\ & 0 \leq X(\omega) \leq G(\omega), U(\omega), V(\omega), x \geq 0, \forall \omega \in \Omega. \end{aligned}$$

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