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Risk neutral and risk averse approaches to multistage renewable investment planning under uncertainty

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ABSTRACT

Strategies for investing in renewable energy projects present high risks associated with generation and price volatility and dynamics. Existing approaches for determining optimal strategies are based on real options theory, that often simplify the uncertainty process, or on stochastic programming approaches, that simplify the dynamic aspects. In this paper, we bridge the gap between these approaches by developing a multistage stochastic programming approach that includes real options such as postponing, hedging with fixed (forward) contracts and combination with other sources. The proposed model is solved by a procedure based on the Stochastic Dual Dynamic Programming (SDDP) method. The framework is extended to the risk averse setting. A specific case study in investment in hydro and wind projects in the Brazilian market is used to illustrate that the investment strategies generated by the proposed approach are efficient.

1. Introduction

Renewable energy has drawn increasing attention in the last years due to technological improvements and environmental demands. Mainly motivated by emission reduction policies, governments have been creating favorable conditions for investment in renewable sources. Those incentives may appear as special tariffs (Boomsma, Meade, & Fleten, 2012), contract environments (Street, Barroso, Flach, Pereira, & Granville, 2009) or other mechanisms. On the other hand, increases in efficiency of such renewable generators, as in the case of wind power turbines, assisted in increasing the profitability of such investments.

Despite the increased profitability, renewable investments still present high risks, since the renewable source usually has some variability and energy market prices are commonly very volatile. In some countries, special regulatory environments have been created in which the government or buyer holds some or all of the risks. The Brazilian regulation initiated in 2004 established two electric energy trading environments: the Regulated Trading Environment (RTE) and the Free Trading Environment (FTE). All agents that are net consumers must back their entire demand by contracts in either of those markets. In the RTE, contracts are negotiated by regularly held lowest price auctions where all of the energy output of a wind power source is contracted at a fixed price and penalties are only incurred if the generator does not fulfill average yearly amounts. The trade-off is that contracts in such environment are habitually low priced, reducing the investors profits. On the other hand, in the FTE contracts are bilateral and can be extensively customized. Renewable sources have special benefits for trading their energy in this free market because special customers benefit from tariff discounts when purchasing from renewable sources with installed capacity of up to 30 Megawatt. Despite opportunities to sell energy at a greater price, current contracts in FTE account for only approximately 28 percent of the total demand, while it potentially could be as high as 45 percent. This difference is largely due to risk aversion. In the RTE there are contracts that account for the variability of the renewable output guaranteeing fixed prices for the yearly average generation of the plants, similarly to feed-in tariffs in other markets. In the FTE the differences between the contracts and the generation must be cleared in the spot market, with price uncertainty, which in turn makes harder to obtain financing and discourage risk averse investors. More information on the Brazilian market can be found in Maceira, Penna, Melo, Moraes, and Duarte (2008), Shapiro, Tekaya, Paulo da Costa, and Pereira Soares (2013) and Street et al. (2012).

In order to mitigate investment risks such as those mentioned above and improve project value usually well-known strategies such as postponing the investment and trading fixed (forward) contracts are used. The value of waiting for better prices is exploited (Boomsma et al., 2012) and there is an emphasis in the value of postponement

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due to uncertain technological advances that may be obtained in the near future (Baringo & Conejo, 2013). A remarkable feature of renewable projects is that often there is some kind of seasonal complementarity of different sources that may provide with natural hedging opportunities (Chakrabarti, Newham, Goodwin, & Edwards, 2011; Street et al., 2009). The main approaches to finding optimal investment strategies in the literature are based on real options theory and on stochastic programming. Real options approaches typically rely on simplifications of the data process, such as a small number of uncertainty dimensions, constrained random processes and arbitrage conditions. Stochastic programming approaches on the other hand present model simplifications such as considering a two stage problem to make the problem tractable, with the disadvantage of limiting the scope of investment policies ((Kazempour & Conejo, 2012), (Kazempour, Conejo, & Ruiz, 2012) and (Street et al., 2009)).

The main contribution of this work is to bridge the gap between both approaches, by proposing a dynamic investment formulation able to model the aforementioned options that is solvable with known multi-stage stochastic programming techniques. We use an approach based on the Stochastic Dual Dynamic Programming (SDDP) algorithm to obtain solutions to the proposed model. In this setting, the uncertain random processes modeling generation and prices may not be considered stagewise independent, as required by the SDDP method. We show how to model dependency by using regression over state variables and augmenting the SDDP method with a Markov Chain. Assumption of stagewise independency of the new state variables allows us to consider equiprobable states and thus making the model implementation straightforward. We resort to the same method used in Shapiro et al. (2013) to extend the approach to account for risk aversion. Finally, we present a case study using data from the Brazilian market to illustrate our framework. Numerical results from the case study show that the proposed approach is able to generate policies that are efficient investment strategies.

The remainder of this paper is organized as follows. The proposed multi-stage stochastic programming investment model is presented in detail in Section 2. The Stochastic Dual Dynamic Programming (SDDP) based solution approach is discussed in Section 3 followed by models for the underlying stochastic processes in Section 4. Section 5 presents the implementation of the proposed framework and its extension to the risk averse setting along with numerical results from a case study. Finally, some concluding remarks are provided in Section 6.

2. The investment problem and formulation

We consider an investor planning to invest in n renewable energy projects (typically wind and hydro generation plants) over a planning horizon of T years. In each decision stage, the investor has to decide whether to invest or not. Along with the investment decision, the investor must choose not only the level of investment in each project but also how much of a fixed price (forward) power delivery contract he will sell to the market. Contracts must be backed by generation capacity, so the investment decision in the contract and all projects is done simultaneously. Since it would be unrealistic to increase (or decrease) the share in some project after the investment decision, we are ultimately deciding the optimal period to invest, as well as the level of investment in the project and contract opportunities. It is clear that, along with the benefit from evaluating the portfolio value, one may always use this approach to independently evaluate each project. The energy surplus (or shortfall) to fulfill the contract is settled in the market by the spot price. The amount of power generated by the projects, as well as the energy spot price, and therefore the forward contract price, is uncertain and modeled as random processes. The overall objective is to determine an investment time and project portfolio in order to maximize the returns given by the difference in revenues from the contract and selling power in the spot market over the planning horizon with the cost of investment. The investor may prefer to defer his investment decision if he expects to obtain better contract prices in the future.

We next develop a multistage stochastic programming formulation of the above described investment problem. We model the generation and price processes on *monthly* basis, however our investment decision stages are *yearly* periods $t = 1, \dots, T$. We will use subscripts τ and t for monthly and yearly periods, respectively. We assume that there are no operational decisions for the generation plants in the projects. That is, plant output will be proportional to the availability of the natural resources. The amount of power (in average Megawatt), generated in a given monthly period τ, is a random data process E_τ^j for each renewable project $j = 1, \dots, n$. The monthly energy spot price (in Dollars/Megawatt-hours) is also a random data process P_τ. If at least one of the plants is located in a different market from the consumer, on circumstances of transmission congestion, prices in the markets will differ. In the considered case, we will not account for this spatial risk, which can be quantified and managed. All price data will refer to a single market. We will discuss the modeling of the stochastic generation and price processes in Section 4. The remaining data for the model are assumed to be deterministic.

At each (yearly) period t there is a binary investment decision x_t. If the investment decision is undertaken, one has to immediately decide what share r_t^j of project j to purchase and also how much of the forward contracts q_t (as a fraction of a maximum amount of Megawatt, denoted D) to sell at the price of the forward contract in January of that year, which we denote as f_t. The modelling of the forward prices is discussed in Section 4. We assume that the share or contracts once determined may not be reviewed in the future. Since each project j represents an individual plant, we are considering that we may partially invest in some plants. This is likely to happen in large infrastructure investments were consortia are build by several companies interested in developing a project and sharing its profits. At least for wind power projects, scalability is not an issue, since they are very modular, given wind power plants involve several turbines in a given site. A small share suggested by the model in those projects might as well indicate that their sizing should be reevaluated.

The forward contracts are customarily backed by physical guarantees related to the output of the plants in the project portfolio. The contract maximum amount D will be associated to some statistic related to the amount of energy produced by the investor's portfolio, typically given by the capacity factor d_j of a project j. Thus the contract amount Dq_t (given by fraction q_t of D) and project shares r_t^j must satisfy the constraints

$$Dq_t \le \sum_{j=1}^{n} d_j r_t^j, \;\; 0 \le r_t^j \le 1, \;\; 0 \le q_t \le 1, \;\; \forall\, t = 1, \dots, T, \tag{2.1}$$

where d_j is the physical guarantee backed by project $j = 1, \dots, n$, and $D := d_1 + \cdots + d_n$.

The costs associated with the investment may be represented by their present value at the time of the investment decision. Monthly revenues are aggregated into the respective yearly revenues by summation. Thus at the investment period t the following cash flow is observed

$$\varrho(1+\rho_c)^{-b} D q_t f_t \sum_{\tau=12(t-1)+1}^{\tau=12t} h_\tau - \upsilon^\top r_t, \tag{2.2}$$

where $r_t = (r_t^1, \dots, r_t^n)$, $\upsilon = (\upsilon_1, \dots, \upsilon_n)$ is the present value vector (in dollars) of the investment costs for each project, h_τ is number of hours in month τ, and ϱ is the present value of an annuity with horizon equal to the project lifetime l. The first term refers to the contract revenue. The stream of payments from the contract is only initiated after the plants in a project are in operation, so it is discounted by the appropriate rate ρ_c by b periods, where b is the build time.