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Decision Support

Comparison of least squares Monte Carlo methods with applications to energy real options

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ABSTRACT

Least squares Monte Carlo (LSM) is a state-of-the-art approximate dynamic programming approach used in financial engineering and real options to value and manage options with early or multiple exercise opportunities. It is also applicable to capacity investment and inventory/production management problems with demand/supply forecast updates arising in operations and hydropower-reservoir management. LSM has two variants, referred to as regress-now/later (LSMN/L), which compute continuation/value function approximations (C/VFAs). We provide novel numerical evidence for the relative performance of these methods applied to energy swing and storage options, two typical real options, using a common price evolution model. LSMN/L estimate C/VFAs that yield equally accurate (near optimal) and precise lower and dual (upper) bounds on the value of these real options. Estimating the LSMN/L C/VFAs and their associated lower bounds takes similar computational effort. In contrast, the estimation of a dual bound using the LSML VFA instead of the LSMN CFA takes seconds rather than minutes or hours. This finding suggests the use of LSML in lieu of LSMN when estimating dual bounds on the value of early or multiple exercise options, as well as of related capacity investment and inventory/production policies.

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1. Introduction

The valuation and management of options with early or multiple exercise opportunities is a fundamental problem in financial engineering and real options (Detemple, 2006; Dixit & Pindyck, 1994; Glasserman, 2004; Guthrie, 2009; Shreve, 2004; Trigeorgis, 1996). A variety of standard and customized stock, interest rate, commodity, energy, and weather options are traded on both organized exchanges and over-the-counter markets (Hull, 2014). When these options give their holders the ability to exercise them one or more times before expiration, the optimization of an exercise policy in the presence of market uncertainty is a key aspect of the valuation and management of these options (Detemple, 2006; Glasserman, 2004; Shreve, 2004). Real options are models of operational flexibility embedded in managerial activities performed in the face of market or operational uncertainty (Dixit & Pindyck, 1994; Guthrie, 2009; Trigeorgis, 1996). Typical applications are the timing of capacity/technology/product investment or divestment decisions, and the switching among inputs or outputs or production modes of manufacturing processes. Common sources of uncertainty include the market value of a completed development project or the levels of input and output prices. The optimization of capacity investment and inventory/production management policies under supply or demand forecast uncertainty (Graves, Meal, Dasu, & Qiu, 1986; Heath & Jackson, 1994; Iida & Zipkin, 2006), possibly combined with market uncertainty (Goel & Gutierrez, 2011; Kouvelis, Chambers, & Wong, 2006), is a critical concern in both operations management (Porteus, 2002; Zipkin, 2000) and hydropower-reservoir management (Nandalal & Bogardi, 2007; Zhao, Cao, & Yang, 2011; Zhao, Zhao, Yang, & Wang, 2013). The modeling of these operational problems shares salient features with the modeling of options with early or multiple exercise opportunities.

Our focus in this paper is on real options, in particular energy real options. Applications include process innovations (Khansa & Liginlal, 2009), manufacturing flexibility (Fontes, 2008; Triantis & Hodder, 1990), capital budgeting (Gamba, 2003), renewable energy investments (Boomsma, Meade, & Fleten, 2012), and commodity and energy acquisition, disposal, processing, production,

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storage, and swing assets (Adkins and Paxson, 2011; Barbieri and Garman, 1996; Boogert and De Jong, 2008; 2011/12; Brandão, Dyer, and Hahn, 2005; Carmona and Ludkovski, 2010; Chandramouli and Haugh, 2012; Cortazar, Gravet, and Urzua, 2008; Devalkar, Anupindi, and Sinha, 2011; Enders, Scheller-Wolf, and Secomandi, 2010; Felix and Weber, 2012; Hahn and Dyer, 2008; 2011; Jaillet, Ronn, and Tompaidis, 2004; Lai, Margot, and Secomandi, 2010; Maragos, 2002; Secomandi, 2010; Smith, 2005; Smith and McCardle, 1998; 1999; Thompson, 2012; 2013; Thompson, Davison, and Rasmussen, 2004; Wang and Dyer, 2010, Arvesen, Medbø, Fleten, Tomasgard, and Westgaard, 2013; Denault, Simonato, and Stentoft, 2013; Mazières and Boogert, 2013; Wu, Wang, and Qin, 2012, Secomandi and Seppi, 2014, Chapters 5–7, Bäuerle & Riess, 2016; Gyurkó, Hambly, & Witte, 2015; Nadarajah, Margot, & Secomandi, 2015).

The modeling of early and multiple exercise options and related operational problems generally gives rise to intractable Markov decision problems (MDPs) with states containing both endogenous and exogenous components. The endogenous part of the MDP state represents the status of the option or the operational system. It is determined by exercise or operational decisions and is low dimensional in several of the discussed applications. The exogenous part of the MDP state is a term structure, such as a commodity or energy forward (futures) curve, a yield curve, or a demand/supply forecast curve. The stochastic dynamics of this term structure are assumed unaffected by option-exercise or operational decisions, and are represented using high dimensional models that share a common mathematical structure (Blanco, Soronow, & Stefiszyn, 2002; Clewlow & Strickland, 2000; Cortazar & Schwartz, 1994; Graves et al., 1986; Heath & Jackson, 1994; Ho & Lee, 1986; Veronesi, 2010). The MDP intractability is thus typically due to two curses of dimensionality: (i) The high dimensionality of the exogenous part of the state space and (ii) the inability to exactly compute expectations of future exogenous state components (Powell, 2011, Section 4.1).

The least squares Monte Carlo (LSM) approach, pioneered by Carriere (1996), Longstaff and Schwartz (2001), and Tsitsiklis and Van Roy (2001), is a prominent approximate dynamic programming (ADP) methodology (Powell, 2011, p. 307) for the valuation and management of early and multiple exercise options (Arvesen et al., 2013; Bäuerle and Riess, 2016; Boogert and De Jong, 2008; 2011/12; Boomsma et al., 2012; Carmona & Ludkovski, 2010; Carriere, 1996; Cortazar et al., 2008; Denault et al., 2013; Desai, Farias, & Moallemi, 2012; Gyurkó et al., 2015; Longstaff & Schwartz, 2001; Smith, 2005; Tsitsiklis & Van Roy, 2001). Similar techniques have been developed for inventory and hydropower-reservoir management problems (Iida & Zipkin, 2006; Wang, Atasu, & Kurtuluş, 2012; Zhao et al., 2011; Zhao et al., 2013), and can be applied to capacity investment and production management settings.

The standard LSM method, known as regress-now LSM (LSMN), addresses the two stated curses of dimensionality by approximating via a linear combination of basis functions the *continuation* function of the MDP formulated as a stochastic dynamic program (SDP). The weights of the basis functions are fitted through least-squares regression on Monte Carlo samples of the exogenous part of the state in a backward recursive fashion. Although convenient for lower bound estimation based on its continuation function approximation (CFA), this method requires executing potentially time consuming nested simulations and optimization when estimating a dual (upper) bound (Glasserman, 2004, Section 8.7, Brown, Smith, & Sun, 2010). A nonstandard LSM variant, proposed by Glasserman and Yu (2004) and known as regress-later LSM (LSML), uses a linear combination of basis functions to approximate the SDP *value* function rather than its continuation function. In this case specifying a value function approximation (VFA) by choosing basis functions of which expectations can be computed in essentially closed form allows avoiding the nested simulations and optimizations that must be performed when estimating a dual bound based on a CFA. Such basis functions include polynomials of term structure elements and prices of call and put options on such elements (Boogert and De Jong, 2008; 2011/12; Boomsma et al., 2012; Broadie and Cao, 2008; Cortazar et al., 2008; Desai et al., 2012; Longstaff and Schwartz, 2001; Tsitsiklis and Van Roy, 2001, Gyurkó et al., 2015).

Despite its appeal, LSML has gone largely unnoticed in the literature. Broadie and Cao (2008) exemplify in passing its application to estimate lower bounds on the prices of multiple exercise (specifically Bermudan max) options. We are not aware of research that compares the performance of LSML and LSMN, or even uses LSML, to value and manage real options.

In this paper we compare LSML and LSMN applied to energy swing and storage options modeled using a common futures term structure model. We use realistic instances to numerically contrast the performance of LSMN/L when obtaining C/VFAs, the computational effort required to estimate lower and dual bounds based on these C/VFAs, and the quality of these bounds. The LSMN/L C/VFAs lead to similarly accurate (near optimal) and precise lower and dual bound estimates. LSMN/L exert comparable effort to obtain their respective C/VFAs and estimate their associated lower bounds. In contrast, estimating the dual bounds using the LSML VFAs instead of the LSMN CFAs takes seconds rather than minutes or hours. This difference is attributable to the nested simulations and the optimizations that must be carried out when using the LSMN CFA to estimate these bounds, but are instead avoided when employing the LSML VFA.

Our findings suggest the use of LSML rather than LSMN when estimating a dual bound on the value of energy swing and storage options. In particular, it may be useful to include the estimation of LSML-based dual bounds as a feature in commercial software packages that use LSMN to obtain lower bounds on the value of operating policies for these options (see, e.g., EnergyQuants, 2016; KYOS, 2013; Matlab, 2015). Potentially, the relevance of our research extends to other options with early or multiple exercise opportunities and capacity investment and inventory/production management models with demand/supply forecast updates.

In Section 2 we formulate our MDP, apply it to energy swing and storage options, and discuss the two curses of dimensionality that arise when attempting to solve this MDP. In Section 3 we present LSMN and LSML and conceptually contrast these methods. In Section 4 we explain how to use their C/VFAs to estimate lower and dual bounds on a real option value. We conduct our numerical study in Section 5. We conclude in Section 6. An online supplement includes Supporting material.

2. MDP, energy applications, and curses of dimensionality

We describe our MDP in Section 2.1. We apply this model to energy swing and storage options in Section 2.2. In Section 2.3 we discuss the two curses of dimensionality that typically make solving this MDP intractable.

2.1. MDP

There are N exercise dates, each denoted as T_i, $i \in \mathcal{I} := \{0, \dots, N-1\}$. The set $\mathcal{I}$ is the stage set. The state of our MDP at stage i is partitioned into *endogenous* and *exogenous* components. The endogenous component is the scalar x_i. It belongs to the finite set $\mathcal{X}_i$ that represents information about the number of remaining exercise rights at stage i. The *exogenous* component is the vector $F_i \in \mathbb{R}^{N-i}$ that represents the option underlying term structure $(F_{i,i}, F_{i,i+1}, \dots, F_{i,N-1})$, where each $F_{i,j}$, $j \geq i$, is the element of the term structure associated with date T_j at time T_i. We define

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