Energy Economics 48 (2015) 295–305

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneco

# Distributed solar renewable generation: Option contracts with renewable energy credit uncertainty

Yaxiong Zeng [a,*], Diego Klabjan [a], Jorge Arinez [b]

[a] Industrial Engineering and Management Sciences, Northwestern University, United States
[b] Sustainable Manufacturing System, General Motors, United States

ARTICLE INFO

*Article history:*
Received 20 January 2014
Received in revised form 18 November 2014
Accepted 22 December 2014
Available online 3 January 2015

*JEL classification:*
Q41
Q42
Q47
Q49

*Keywords:*
Real option
Renewable energy
Solar generation
REC market

ABSTRACT

Solar energy is rapidly emerging thanks to the decreasing installation cost of solar panels and the renewable portfolio standard imposed by state governments, which gave birth to the Renewable Energy Credit (REC) and the Alternative Compliance Payment (ACP). To make profits from the REC market in addition to reduced energy costs, more and more home and business owners choose to install solar panels. Recently, third-party financing has become a common practice in solar panel investments. We discuss optimal timing for the host to potentially buy back the solar panels after being installed for a period of time and how to incorporate the optimal timing into a power purchase agreement between the host and the third-party developer. Because the REC price is a major source of uncertainty and also due to the ACP capping the REC price, we first propose a REC price forecasting model that specifically considers the ACP values. Then by a modified real option structure, we model the buyback contract as a real option and solve it with an approximate dynamic program based Monte Carlo simulation method. We find that as the ACP value increases, the value of the buyback option also increases under optimal timing. The method used does not only apply to solar projects but also to other distributed renewable projects that are third-party financed, such as wind generations.



## 1. Introduction

In recent years, global warming has been increasingly acknowledged as a threat to long-term human survival. Many countries have thus set up targets concerning emission limitations or reductions of greenhouse gases: the European Union aims at a 20% reduction below the 1990 baseline by 2020 (UNFCCC, 2008) and the United States offers a goal of a 17% reduction below the 2005 level by 2020 (U.S. Department of Energy, 2009). To attain these goals, renewable energy technologies are being widely adopted to reduce the reliance of energy on fossil fuels.

In the United States, in 2011 renewable energy accounted for 9% of total primary energy consumption, with hydroelectric (35%), wood (22%), biofuels (21%) and wind power (13%) as major renewable sources (EIA, 2012). The solar market is now rapidly expanding as a result of historically high photovoltaic prices and by the financial incentives from the federal government, states and utilities. From the 2012 U.S. Solar Market Insight report, photovoltaic installations totaled 3313 MW, up 76% from 2011 with an estimated market value of $11.5 billion (SEIA/GTM Research, 2013).

One important aspect in the solar market is the Renewable Energy Credit (REC). As of 2013, the Renewable Portfolio Standard (RPS) is implemented in 30 U.S. states (including District of Columbia). Under such a policy, local utilities and load-serving entities are obligated to procure a specified fraction of their electricity as renewable energy. As a market response to RPS, the REC trading programs are initiated in most of the 30 states. Eligible renewable power producers receive a REC for each MWh of renewable energy generated. When electricity providers cannot meet the mandatory requirement from their own power facilities, they can in turn purchase RECs from renewable generators to comply with the RPS. The unit of REC price is $/MWh. Specifically, 17 out of the 30 states adopted detailed RPS targets to ensure solar power comprises a minimum fraction of the renewable mix, resulting in the creation and trading of the Solar Renewable Energy Credit (SREC). If the power supplier fails to obtain adequate credits, i.e. fails to meet the RPS, it is then subject to a penalty called the Alternative Compliance Payment (ACP) per MWh. In the solar case, the supplier is subject to the Solar Alternative Compliance Payment (SACP). Generally, SACP caps the SREC price. Otherwise, the obligated entity would prefer to pay the penalty, which is the mechanism of last resort to achieve compliance with the RPS. As the solar market continues to grow, the SREC trading program provides a driving incentive for home and business owners to install photovoltaic panels to satisfy their own electricity needs and financially benefit from selling SRECs.

* Corresponding author at: 2145 Sheridan Road, Evanston, IL 60208, United States.
*E-mail addresses:* yaxiongzeng2015@u.northwestern.edu (Y. Zeng), d-klabjan@northwestern.edu (D. Klabjan), jorge.arinez@gm.com (J. Arinez).

http://dx.doi.org/10.1016/j.eneco.2014.12.013
0140-9883/

In residential or commercial sites, direct ownership of solar panels is not a common practice. Instead, third party financing is taking off across the U.S. For instance, the 2012 U.S. Solar Insight Report pinpoints the ongoing third-party solar revolution. Specifically, over 50% of all new residential installations in most major residential markets are from third-party-owned systems. The report also forecasts that the momentum will last. Usually, a third-party developer designs, installs, owns, operates and maintains solar panels on the user's roof and the user or host procures electricity from developer-owned solar panels. The user pays the developer according to a lease or Power Purchase Agreement (PPA). In the lease contract, home or business owners pay a monthly flat fee to the third-party developer. In the PPA, the host pays based on its electricity usage and according to a fixed rate or a rate with a fixed annual escalating factor. In both settings, the host does not pay for the panel installation or maintenance while it is the developer who incurs these costs. We particularly study the PPA setting, where the host buys all the electricity generated from the panels as negotiated in the contract.

Although the contract based on third-party financing can bring electricity with low and predictable costs, it prevents the host from making profits by selling RECs since they are owned by the third-party entity because they own the installation. The customer can buy back the panels at a later time (see NREL, 2009). However, when to buy back the panels has not yet been studied. Thus in this paper, we discuss optimal timing of the buyback option by the host, in which the host buys the third-party owned solar panels at a particular time and price, and the REC ownership transfers from the developer to the host after panel buyback. The timing decision from our analysis is valuable to both the third-party developer and host. Grounded on the analysis, the two parties can develop the PPA and integrate the best timing decision into the contract. Ultimately, the buyback problem is a real option because it focuses on the exercise opportunity during a predetermined period.

Uncertainties involved in the buyback option result from fluctuations of REC prices, the electricity price, electricity demand by the user, and the value of the solar panels. As the REC markets continue to grow in the United States and worldwide, changing REC prices will have an increasing effect on the optimal investment timing decision. In this paper, we first introduce a new financial model to forecast REC prices, which have a lower bound of zero and upper bound of the ACP value. Results show that our model outperforms the existing Geometric Brownian Motion (GBM) forecasting model. Forecasted REC prices are then incorporated in the cost–profit analysis of the solar investment. After the buyback option is exercised, the pattern of the cash flow changes due to REC sales. We thus model the investment timing problem as a real option by proposing a new option structure. We solve the model using a Monte Carlo simulation method based on approximate dynamic programming (ADP). In essence, our real option structure does not rely on sophisticated financial mathematics due to inherent complexity and can provide decision insights under different combinations of uncertainties.

In this paper, we consider the host to be a non-power generating company. We only discuss solar projects, but the methodology can be adapted to other distributed renewable generations. For example, on-site wind generation is also applicable to our analytical framework, since it has an equivalent REC market and a similar third-party financing structure. The main contributions of this paper are as follows.

1. A new REC forecasting method that specifically takes ACP values into account;
2. A new real option framework that can handle different patterns of cash flow before and after the option is exercised;
3. A developer–host contract that explicitly considers optimal buyback timing, the first of its kind in distributed renewable generation;
4. A case study that solves a problem of a real-world company.

The structure of this paper is as follows. Section 2 provides a literature review. Section 3 introduces the new REC forecasting model and compares it with existing models. Section 4 exhibits the model of the investment timing problem as a real option and it provides the solution methodology by means of the least square ADP algorithm. Section 5 discusses the results from the Monte Carlo simulation with three case studies. Section 6 draws conclusions and suggests relevant future work.

## 2. Literature review

An important model in our work is the discounted cash flow (DCF) model. When assessing an investment project, the DCF model is chosen traditionally. The model discounts the cash flows of the project to present time. If the obtained net present value (NPV) is positive, the project is economically viable. Due to its simplicity, it leads to rigid managerial decisions. It assumes that the future cash flows have no variability, and the decision is simply to invest now or abandon the investment. These two drawbacks contradict the current investment styles characterized by uncertainties and dynamic decisions. As a remedy, the concept of real option has been proposed, which has been researched in a variety of disciplines during the last three decades. Essentially, it serves as an extension to the DCF model. Several textbooks have been published to comprehensively introduce the concepts, theories and methods in real option studies (Dixit and Pindyck, 1994; Trigeorgis, 1996; Amram and Kulatilaka, 1999; Mun, 2002).

Before year 2000, in the energy sector, most of the real option literature applies to the oil industry. Because of the deregulation of the electricity market in the mid 1990s, real option principles began to be widely adopted in the analysis of electricity relevant topics such as electricity markets and power system investments. However, it is not until the last decade that the real option theory has been applied to the renewable energy field. The first paper by Venetsanos et al. (2002) presents a framework to assess renewable energy projects by real options and illustrates the possible uncertainties under deregulated energy markets. The paper models a Greek wind energy project as a real option and evaluates it by the Black–Scholes model, different from our ADP approach.

There are two popular methods in renewable real option analyses: the partial differential equation (PDE) method and the dynamic programming (DP) method. Usually, the PDE method requires an advanced understanding of stochastic models and financial mathematics. It is also not easy to analyze a real option that allows an early exercise using PDE, similar to an American call option. As another method, DP follows a recursive pattern to optimize decisions that influence future cash flows. Unlike PDE, the DP approach makes intermediate values and decisions readily available (Fernandes et al., 2011). In DP applications, a full stochastic DP is sometimes used, but the simplest and most frequently used model is the lattice model. By calculating risk neutral probabilities and up and down factors, it is possible to almost always identify the basic structure from any real option and construct a corresponding lattice model (Mun, 2002). For example, Munoz et al. (2009) use a trinomial lattice model to evaluate the option to invest in a wind power generation project and demonstrate the probabilities of “invest now,” “wait,” and “abandon,” while we only consider one option over the entire time horizon — in which year we should invest. The main problem with the lattice model is the difficulty to deal with multiple uncertainties. It needs multiple variables to represent different uncertainties, and thus the number of nodes grows exponentially with the dimension of uncertainties. Furthermore, to approximate the stochastic process accurately, it requires a high-dimension tree or infinitesimal time intervals. These two factors make it computationally expensive in the attempt to model complex problems with several uncertainties and to retain a satisfactory level of approximations of endogenous stochastic processes.

As a result, we adopt a Monte Carlo simulation and optimization method to solve our model. Unlike the PDE method, it requires less mathematical sophistication and can easily handle early exercise situations. In contrast to the lattice model, it better copes with stochastic processes, regardless of the dimension of uncertainties. In this study, we