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Optimal operation of a solar-thermal power plant with energy storage and electricity buy-back from grid

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ABSTRACT

Optimization of time-variable operation to maximize revenue through selling and purchasing electricity to/from the grid is presented for a thermal energy storage system. Time-variable electricity prices and electricity buy-back from the grid to re-charge the energy storage is considered by adding electric heaters to the CSPonD concept [Slocum et al., [15]]. System-level models are developed and optimization of the design and operation is performed. Three case studies are considered: i) time-variable operation without electrical heating under time-invariant electricity price; ii) operation under time-variant electricity price without electric heaters; iii) operation under time-variant electricity price allowing charging of the pond using the grid electricity. These demonstrate the effect of time-invariant versus time-of-use feed-in-tariff. Two hourly price profiles are considered, representing a moderately and highly fluctuating price profile respectively. Uncertainty of the cost function is indirectly addressed: the approach optimizes for the expected value of profit. The results show significant increase in the revenue when adding electric heaters. Under the moderately fluctuating electricity price, the use of heaters increases the revenue significantly, compared to the same case with no electric heaters considered. In the case of highly fluctuating electricity price, the use of heaters more than doubles the revenue.

1. Introduction

Two key concerns with the use of renewable energy sources (RES) to produce electricity at a large scale are the low reliability and high levelized cost of electricity (LCOE). Inclusion of energy storage with RES may increase reliability and decrease LCOE. However, when comparing different RES technologies with and without energy storage, LCOE is not a suitable metric since it ignores dispatchability and the time of day (TOD) the electricity is generated, two of the key characteristics for asset generation [1], e.g., photovoltaics (PV) without tracking versus concentrated solar power (CSP) with storage, lower LCOE does not imply higher revenue. Thus, time-variable production of renewable electricity systems is an important issue as both the energy source and the electricity demand are time-variable. This article addresses some key questions with respect to the time-variable operation of renewable systems. First and foremost, *is time-variable operation of renewable energy systems feasible?* Assuming so, *can a renewable system be operated in an on-demand way? Will time-variable operation result in an appreciable increase in revenue, or the ability to meet a time-variable demand and the peak electricity load? Is it economical to purchase electricity back from the grid at times of low prices and use it to recharge the storage?* System-level models and nonlinear programming (NLP) with dynamics embedded is used to optimize the revenue of a solar-thermal energy system under alternative simulated market conditions. Optimization of operation is considered in the field of conventional power producers [2–4]. In solar-thermal power plants, operation strategies have been employed to increase the average thermal efficiency [5–7] and also to maximize revenue under a fixed plant design, so that the power plant is consequently run with a price-driven strategy [8]. Therein, a methodology based on electricity pricing and weather forecasting is shown on how to set up an economically optimized bidding strategy at the energy exchange, which takes the solar resource and the price information into account.

There is a number of thermal energy concepts tested in solar energy plants around the world. Two-tank system with molten salt mixtures [9–12] is among the most developed and tested concepts. Although the collector cost is the single largest cost of solar-thermal

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Nomenclature

Latin letters

$\dot{m}_{\text{cold to hot}}$	mass salt flow rate from the cold to the hot salt tank [kg/s]
$\dot{m}_{\text{hot to cold}}$	mass salt flow rate from the hot to the cold salt tank [kg/s]
$\dot{Q}_L$	thermal losses of the thermal storage system [MW]
$\dot{Q}_{\text{out}}$	total heat transfer rate out of the thermal storage system into the power cycle [MW]
$\dot{W}_{\text{purchased}}$	electric power purchased from the grid [MW]
$\widehat{c}$	time-weighted average electricity price [$/kWh]
c	electricity price [$/kWh]
C_p	specific heat capacity of salt $[\text{kJ}/(\text{kg}\cdot\text{K})]$
l	simulation length [h]
$m_{\text{hot tank}}$	content of salt in the hot salt tank [kg]
Obj	objective function [$]
t_s	sunrise time [h]
$T_{\text{cold tank}}$	temperature of the cold salt tank [K]
$T_{\text{hot tank}}$	temperature of the hot salt tank [K]
T_{lid}	temperature of the lid [K]
T_{return}	temperature of the salt flow to the cold salt tank from the power cycle heat exchanger [K]
T_{salt}	temperature of the salt [K]
CSP	concentrated solar power
CSPonD	concentrated solar power on demand
DAE	differential algebraic equation
DAM	Day-Ahead Market price
ERCOT	Electric Reliability Council of Texas
LCOE	levelized cost of electricity
NLP	nonlinear programming
PV	photovoltaics
RES	renewable energy sources
RSD	relative standard deviation
RTM	Real-Time Market price
TOD	time of day
L	Number of main finite elements
K	Interpolation polynomial order

Greek letters

η_{field}	collector field efficiency
η_{power}	power block efficiency

plants, the additional cost of two-tank thermal energy storage system is significant. As such, alternative designs such as thermocline and rafted thermocline [13,14] have been investigated. Herein the concentrated solar power on demand (CSPonD) concept is considered, an integrated volumetric solar energy receiver and thermal storage system proposed by Slocum et al. [15].

The use of CSPonD for cogeneration concepts (e.g., power production and water desalination) was investigated in Refs. [16,17]. Therein, the focus was mainly on the optimization of design and constant power generation strategies were considered. Herein, optimization of time-variable operation is considered for electricity generation that uses the solar energy collected by CSPonD. More specifically, the main purpose of the present study is to assess the potential of a solar-thermal generation system considering fluctuating electricity prices. The nominal power output is 35 MWe, with a thermal energy storage capacity of 15 h. In addition, the usage of 20 MW electric heaters to charge the thermal energy storage when electricity prices are negative or sufficiently low, i.e., purchasing back the electricity from the grid is considered. While the concept of the electricity buy-back has been previously studied [18–20], the concept of optimization of time-variable operation with inclusion of energy storage has not been studied previously, to the best knowledge of the authors. These two designs (with and without electric heaters) considered herein are fixed before the operation is optimized. Negative electricity prices have occurred recently in many places including Germany, for instance, with prices as low as −0.5 €/kWh [21], or in West Texas where the Real-Time Market (RTM) price of electricity was negative for 23% of April 2009 [22]. Herein, two electricity profiles are considered. These two profiles differ in the variability and absolute prices; in particular the relative standard deviation (RSD) of the electricity price is very different. RSD is defined as the ratio of the standard deviation of hourly prices divided by the average electricity price. The first one is a fictitious electricity price distribution that fluctuates moderately, with an average price, $\widehat{c}$, of 0.26 $/kWh and an RSD of 7.1%. The second price profile fluctuates highly, including negative electricity prices, and is obtained from the RTM electricity prices in April 2009 in West Texas [23]. Optimal operation of two periods is studied under this real electricity price profile: firstly, only one day is considered, the 22nd of April, with an average price, $\widehat{c}$, of 0.00175 $/kWh and an RSD of 183%, in order to compare it with the moderately fluctuating electricity price profile. The day chosen is by no means an average day; however, there are days of more fluctuating electricity prices including days with negative average price. Secondly, optimal operation for an entire week is considered, from the 20th to the 26th of April, to reduce the effect of daily electricity price patterns on the conclusion. In this case, the average price, $\widehat{c}$, is 0.0044 $/kWh and the RSD is 210%. It is worth noting that in the Electric Reliability Council of Texas (ERCOT) [23], where the prices are obtained, the RTM does not change significantly with the Day-Ahead Market (DAM). For example, in April 2009, only 2.5 h have price corrections from the DAM to the RTM, and they are not significant (maximum of 25% change, whereas the majority of them are a few cents). Thus, these differences have no significant effect in the final results. Moreover, a well-established way to dealing with uncertainty is via stochastic optimization, wherein the expected value of the objective function is optimized for [24–28]. In contrast herein the optimization is performed assuming the expected value for the uncertain electricity price. However, in Appendix A it is shown that these two approaches are equivalent. As aforementioned, a fixed design is considered and the operation is optimized for. The cost function is uncertain, and all decisions are made before the uncertainty is resolved. In other words the stochastic program is a single-stage problem. Moreover, the uncertain electricity price directly and linearly affects the objective function but not the constraints. Consequently, an analytical expression for the expected value of the objective function can be found: the expected value of the objective function is the objective function using expected values for the electricity price. In other words the optimization using nominal values is equivalent to the stochastic optimization.

2. System description and models

A system-level schematic of the design considered herein is shown in Fig. 1. The heat withdrawn from the CSPonD is used in the steam generator of a steam cycle. The models calculate the time-variable operating conditions including solar energy input to the