COORDINATED TRADING OF SOLAR AND THERMAL ENERGY INCLUDING V2G SERVICES

Muhammad W. Khalid, Ali T. Al-Awami
King Fahd University of Petroleum and Minerals
Dhahran, Saudi Arabia
iwaqas@kfupm.edu.sa, aliawami@kfupm.edu.sa

ABSTRACT
The minimum up/down time constraints of the thermal units expose them to the risk of operating at low benefits or even at loss at some periods. Also participants with renewable energy sources (RES) are at risk due to their uncertain resources. Energy trading in day-ahead energy market is already risky due to undecided energy and imbalance prices and load demand, whereas participation of RES makes it more risky. Coordinated trading of thermal with RES can mitigate this risk. Moreover, responsive demand can also be used for this purpose. In this paper, the case of a utility that have solar and thermal generators and use electric vehicles (EVs) as responsive demand is investigated. A bidding strategy is proposed for solar-thermal coordination while providing charging EVs through unidirectional vehicle-to-grid (V2G) services. The objective is to maximize the total expected profits of the utility while controlling its risk. The problem is devised as a stochastic mixed integer linear programming (MILP) with four random/stochastic parameters. A realistic case is developed for comparing uncoordinated with coordinated solar-thermal trading utilizing V2G services. Results show that coordination gives rise to higher expected profits and lower risk.

KEY WORDS
Coordinated bidding strategies, Mixed Integer Linear Programming (MIP), Profit maximization, Renewable Energy Sources (RES), Vehicle to grid services (V2G).

1. NOMENCLATURE

A. Index:
i EVs
t Bidding hours
s Scenarios
g Thermal units
r Solar plants

B. Variables and functions
$S^\text{act}$ / $S$ Actual/bid of solar power output
$p^\text{act}$ / $p$ Actual/bid of thermal power output
$L^\text{act}$ / $L$ Actual/forecasted Load
$\rho$ Energy market price
$\rho^u$ / $\rho^l$ Over/under generation imbalance penalty
$u$ Thermal unit commitment status
POP Optimal charging schedule of EVs
MinAvP Minimum Available power of EVs
MaxAvP Maximum Available power of EVs
PD Actual power draws of EVs
PF Total expected profit
IMBup Over generated energy
IMBdn Under generated energy
CVaR Conditional value at risk at $\alpha$ confidence
$\gamma$ and $\eta$ Auxiliary variables for CVaR

C. Constants
prob Probability of each scenario
R Utility charging rate
StUp Start up cost of thermal units
RD/ RU Thermal unit ramp down/up rate
MinUp Thermal unit minimum up time
InitUp Minimum initial up time of thermal unit
$a,b,c$ Coefficients of thermal units
$P^\text{max}$ / $P^\text{min}$ Thermal power output limits
$s^\text{max}$ Solar plant maximum capacity
$Av$ Availability of EVs
MaxC Maximum charge of EV
MaxPD Maximum power draws of EV battery
SOC _l Initial charge of EV
Trip Reduction in SOC due to commute
T _Trip Time of commute

2. INTRODUCTION

2.1 Background

Utilization of fossil fuels in power generation and transport systems causes a significant amount of greenhouse gas emissions and environmental pollution. To overcome the problems associated with generation of electricity from fossil fuels, Renewable Energy Sources (RES) can be included in the energy mix [1], [2]. In general, electricity market deregulation and the development of the distributed generation (DG) and smart grid (SG) technologies are promoting the use of RES in power generation [3].

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Conventional thermal units, though controllable, are vulnerable to the uncertainty in energy market prices. Additionally, minimum up/down time constraints of thermal units cause them to be exposed to the risk of operating at low profits or even at loss at some periods. Some other kinds of thermal units, like reciprocating engines, can have nearly zero minimum up/down time, fast ramping rate, and almost zero minimum power output, but they usually have high operating costs [4]. In contrast, RES power producers are subjected to uncertainty in both the system prices as well as resource availability that cause supply-demand imbalance. Hence, it’s a great challenge to sell energy as several electricity markets impose imbalance penalties.

Coordination of RES with thermal units would be profitable for both. Thermal units get benefit by shutting down during low market price hours and avoiding their low profit/loss periods. RES are beneficial by avoiding high imbalance penalties as a result of coordination with thermal units. Benefits of thermal coordination with wind have been discussed thoroughly in [4]. However, solar thermal coordination is also beneficial particularly during mid day hours, when solar power output is maximum and load is at its peak, by switching off the high incremental cost thermal units that are running with low profitability due to their operating constraints. This is particularly useful for summer-peak systems, such as that of Saudi Arabia.

Moreover, the use of Electric Vehicles (EVs) is increasing rapidly because of their high efficiency and lower environmental effects over traditional vehicles [5], [6]. The extensive use of EVs will bring new challenges to the operation and scheduling of power system. For instance, mass unregulated charging of EVs can cause energy shortages in power grid. Vehicle to grid (V2G) technique turns out to be effective for the integration of EVs with the grid. Its purpose is to provide ancillary services and flexible/responsive load demand. In bi-directional V2G, flow of power can be in both directions. Unidirectional V2G is more popular because it requires less hardware implementation and does not degrade battery life [7]. V2G also allows EV owners to charge their cars at lesser cost.

2.2 Literature Review

Several approaches of trading thermal energy in short-term electricity markets have been given in the literature. In [8-11] thermal energy trading includes equilibrium models, but does not take account of unit commitment decisions. Price-based unit commitment is considered in [12-15], but spot market price uncertainty is not considered. The most comprehensive work on thermal trading is done in [16] where the optimal bid strategy for a producer with several thermal units is devised as a MIL stochastic program. Price uncertainty, unit commitment decisions, thermal constraints was considered while mitigating risk.

Coordination of thermal units with wind energy to control trading risk is discussed in several works. Most comprehensive study is done in [4], at which market prices uncertainties and wind power output stochastic behavior is considered. The purpose is to maximize the total expected profit of wind thermal coordination while controlling its risks. The conditional value at risk (CVaR) is used as a risk controlling tool.

Several smart charging algorithms have been proposed in recent literature to get regulated charging profile without negative impact on grid [7], [17], [18]. These works use V2G assets to compute bidding capacities to be used in energy market in deterministic way. Coordination of V2G with thermal or RES is not considered in these works, though.

Coordination of V2G scheduling with deterministic thermal unit commitment including wind/solar energy source is discussed in [19]. Results show that total operating cost is decreased due to V2G coordination with the system. Coordinated trading of energy with V2G services is described in [5]. Optimization is run to maximize the expected profit. Results show that profits are increased with considerable reduction in emissions while trading risks are minimized. Uncertainties of stochastic variables and risk aversion behaviour are included [19].

2.3 Approach

In this work, a bidding strategy for the solar-thermal coordination is proposed for the short term power market. This will be also coordinated with unidirectional V2G services. The case under investigation comprises of a utility having solar and thermal generation and feeds a load with a large number of EVs through V2G services. The utility is also acting as an aggregator for the EVs. MILP is used to model this optimization problem that determines the optimal thermal commitment schedules, EV charging profiles and coordination benefits, while mitigating the trading risk. For risk control, the CVaR is used. It gives the expected profits for the least (1-α) profitable scenarios, where α is the confidence level. Spot market prices, imbalance prices, loads, and solar irradiations are considered as stochastic variables. Solar power output limits and 11 non-bidding hours (8 P.M to 6 A.M) constraints are also included. Thermal Unit constraints of minimum up/down time, initial up/down time, ramping rate and output power limits are considered, too.

3. PROBLEM DESCRIPTION

This optimization problem is devised as a two-stage mixed integer stochastic program that is usually used to cope with the uncertainties. In SP, several scenarios of the stochastic variables are generated and a scenario tree is built [4, 5]. These scenarios are mutually exclusive of each other. A probability of occurrence is assigned to each scenario. Two sets of decision variables are used: “here-and-now” and “wait-and-see”. First stage decisions
are hourly bids of solar and thermal plants and thermal unit commitments that are submitted to the market that would maximize profits. Second stage decisions are thermal power dispatches and charging schedules as they depend on the first stage decisions.

Solar irradiation scenarios are generated using a heuristic technique presented in [4]. ARIMA modelling is used to generate market price scenarios, as in [20]. Thousand of scenarios are required to represent each stochastic variable. But to use all of them is not computationally efficient. Therefore, scenario reduction techniques are important to make the optimization problem tractable. The scenario reduction is used to reduce the large number of scenarios without significantly changing the statistical attributes of the original scenario sets. The algorithm proposed in [21] is used for this purpose.

A pool based power market that is organized as a day-ahead market is considered. It is also assumed that this power generation system is a "price taker" so that the market price can be taken as an exogenous parameter [4, 20]. Hourly bids for the 24 hour period of the following day are submitted at 10:00 AM.

4. MATHEMATICAL FORMULATION

This section provides the detailed mathematical formulation for the optimization problem.

4.1 Coordinated Trading of Solar Thermal Energy Including V2G

The objective function for coordinated solar thermal strategy is as follow,

\[
\text{Maximize } E[PF] 
\]

\[
E[PF] = \sum_{s,t} \text{prob}_{s,t} [PFTH + PFSLR_s + PFEV_s + PFIMB_s] 
\]

(1)

\[
PFTH = \sum_{g,s} \left( p_{reg}^s - C_e^s \right) \left( \max(0, StUp_{g,s} (u_{tg} - u_{tg+1})) \right), \forall s 
\]

(2)

\[
PFSLR_s = \sum_{g,s} p_{reg}^s S_{reg}, \forall s 
\]

(3)

\[
PFEV_s = \sum_{s,t} R_i (L_{s,t}^o + \sum_{g,s} PD_{g,s}) - p_{reg}(L_i + \sum_{g,s} POP_{g,s}), \forall s 
\]

(4)

\[
PFIMB_s = \sum_{g,s} p_{reg}' IMB_{up} - p_{reg}' IMB_{dn}, \forall s 
\]

(5)

Thermal Units’ per-scenario profits are given by (3). That includes the revenue of selling energy in market, production cost and startup cost for each generator. Equation (4) represents the profit of selling solar energy for each scenario. Operating cost of solar plants is almost negligible so they are not included, whereas maintenance costs can be included easily by adding a constant factor. Equation (5) has two terms. The first is the utility revenues paid by load end users and EV users. Note that power draw by EV users is multiplied by \( \gamma < 1 \) as an incentive. The second term represents the cost of energy purchased from market. Imbalance energy penalties for each period and scenario are formulated in (6). For any given period or scenario one of the two terms can be non-zero. These can be expressed mathematically as given,

\[
IMB_{up} + IMB_{dn} = \psi_{ts} 
\]

(6)

\[
IMB_{up} \begin{cases} \psi_{ts} & \text{if } \psi_{ts} \leq 0 \\ 0 & \text{otherwise} \end{cases} 
\]

(7)

\[
IMB_{dn} \begin{cases} \psi_{ts} & \text{if } \psi_{ts} \geq 0 \\ 0 & \text{otherwise} \end{cases} 
\]

(8)

Where,

\[
\psi_{ts} = \sum_{g,s} (P_{reg}^s - P_{reg}^{max})^+ + \sum_{g,s} (S_{reg} - S_{reg}^{max})^+ + \sum_{g,s} (POP_{g,s} - PD_{g,s}) + (L_{reg} - L_i) 
\]

(9)

4.1.1 Operating Constraints

Imbalance constraints models have been proposed in many works. The most computational efficient modeling is given in [4, 20], and it is given below.

\[
IMB_{dn} - IMB_{up} = \psi_{ts} 
\]

(10)

\[
0 \leq IMB_{up} \leq \sum_{g,s} P_{reg}^{max} + \sum_{g,s} S_{reg}^{max} - \sum_{g,s} PD_{g,s} 
\]

(11)

\[
0 \leq IMB_{dn} \leq \sum_{g,s} P_{reg}^{min} + \sum_{g,s} S_{reg}^{min} - \sum_{g,s} MnAP_{g,s} 
\]

(12)

For each hour and scenario, solar unit bid should be within limits and have 11 non-bidding hours, since it cannot produce energy when irradiations are low in night hours.

\[
0 \leq S_{reg} \leq S_{reg}^{max}, \forall t, s, r 
\]

(13)

\[
S_{reg} = 0, \forall t = 7 PM \ldots 6AM, \forall s, r 
\]

(14)

The actual power output and bidding power limits and ramp rate limits of each thermal unit are shown in (15) – (17).

\[
P_{reg}^{min} \leq P_{reg} \leq P_{reg}^{max}, \forall t, s, g 
\]

(15)

\[
P_{reg}^{min} \leq P_{reg} \leq P_{reg}^{max}, \forall t, s, g 
\]

(16)

\[
-RD_{g} \leq P_{reg} - P_{reg}^{max} \leq RD_{g}, \forall t, s, g 
\]

(17)

Efficient modeling of minimum up time constraints are given in [4, 16], as shown in (18) – (20). Minimum down time constraints can be modeled in the same way.

\[
\sum_{g,s,t} \left( 1 - u_{tg} \right) = 0, \forall g 
\]

(18)

\[
\sum_{g,s,t} u_{tg} - \sum_{g,s,t} u_{sg} \geq \text{InitUp}_{g,t} + 1 - \text{MinUp}_{g}, \forall g, t 
\]

(19)

\[
\sum_{g,s,t} u_{tg} - \sum_{g,s,t} u_{tg} \geq 0, \forall g, t 
\]

(20)
4.1.2 EV Charging Constraints

Battery capacity constrained for EV charging optimization are modeled in (21)–(23). Equation (21) ensures that the battery is at least 99% charged before the first trip and the end day SOC should be as high as initial SOC (25). Equation (22) limits the total energy added to the battery to be less than the battery capacity for all $x$ number of trips. Reduction in battery SOC from commuting due to all trips is modeled in (23). Equation (24) limits the battery charge rate. Bidding limit constrains for each EV Power draw are given in (26).

$$0.99 \times \text{Max}_C \leq \sum_{t \in T} EF \times PD_s + \text{SOC}_s - I - (x - 1) Trip \leq \text{Max}_C, \forall s, i \quad (21)$$

$$\sum_{t \in T} EF \times PD_s + \text{SOC}_s - I - (x - 1) Trip \leq \text{Max}_C, \forall s, i \quad (22)$$

$$0 \leq \text{Max AvP}_n + \text{POP}_n \leq \text{Max DP}_n \times \text{Av}_t, \forall t, i \quad (24)$$

$$\sum_{t \in T} EF \times PD_s - 4 Trip \geq 0, \forall s, i \quad (25)$$

$$\text{POP}_n - \text{Min AvP}_n \leq \text{PD}_n \leq \text{POP}_n + \text{Max AvP}_n, \forall t, s, i \quad (26)$$

$$0 \leq \text{Min AvP}_n \leq \text{POP}_n, \forall t, i \quad (27)$$

4.2 Risk Averse Formulation

CVaR is used in this work to mitigate risk. It can be included in the objective function as a linear term [20]. Hence, the objective function is changed to

$$\text{Maximize} \ E[P F] + \beta \text{CVaR}_n \quad (28)$$

where,

$$\text{CVaR}_n = \zeta - \left(1 - \frac{1}{\alpha} \right) \sum_{s, i} \text{prob}_n \eta_s \quad (29)$$

The following constraints are also included [21]:

$$-\{PF_{TH} + PF_{SLR} + PF_{D} + PF_{IMB}\} + \zeta - \eta_s \leq 0, \forall s \quad (30)$$

$$\eta_s \geq 0, \forall s \quad (31)$$

where, $\beta$ is a weighting parameter of the risk aversion attitude of the power producer, for risk neutral attitude $\beta = 0$.

5. CASE STUDY

A realistic case study is considered, in which a utility bids in a pool-based day-ahead energy market with the objective to maximize its profit while fulfilling constraints. This utility has three thermal units with a total capacity of 195 MW, and a solar plant with 100 MW max generation. It also serves loads consisting of large numbers of EVs.

Solar power output mainly depends on solar irradiation and temperature. The effect of temperature on panel power output is neglected in this study as it is not the primary factor. By including uncertainty in solar irradiation we can generate scenarios for the solar power output using the technique given in [4]. It requires hourly distribution of solar irradiation given the forecast and its standard deviation along with ramp rate distribution. Hourly mean and standard deviation of solar irradiation are forecasted using 6 months data (January – June 2007) taken from [22]. Standard deviation of solar irradiation ramp rate is considered to be 140 Watt/m² with almost zero mean; these parameters are calculated using data from [18]. A set of 1000 scenarios for solar irradiation profiles is generated using these parameters. Output power of PV panel corresponding to each scenario is calculated using [23].

Energy price and imbalance price scenarios are generated using ARIMA model. The historical data required to forecast and to generate scenarios is taken from [24] for a three-month period (January to March 2008). Using these techniques, 1000 scenarios for energy and imbalance prices are generated.

To generate load demand scenarios, we consider the nominal (expected) load profile as shown in figure 1. To include uncertainty, a total of three profiles are considered (expected, low and high). Low/high profile is 3% lower/higher than the expected load profile [5].

6. RESULTS AND ANALYSIS

6.1 Solar Thermal Coordination

In this case, coordination benefits of thermal units with solar plants are considered with $\beta = 0$ (risk neutral case).
Uncoordinated thermal and solar are simulated and their expected profits are compared with the coordinated case. Note that, uncoordinated solar is simulated for 13 hours (6 A.M to 7 P.M.) as solar plant cannot bid at night. Comparison shows that coordination gain is as high as 1.05% as is shown in table 1.

Unit commitments for coordinated and uncoordinated case are shown in table 2 and table 3. It can be noticed that unit 3 is committed more often in the coordinated case as compared to uncoordinated thermal bidding which shows that it is being used to coordinate with solar whenever there is an imbalance down in the system. Unit 3 can ramp up from 0 MW to almost its maximum value 50MW in one hour. Such a unit is suitable for coordination purposes.

<table>
<thead>
<tr>
<th>Table 1: Solar thermal coordination gain</th>
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<tbody>
<tr>
<td>Cases</td>
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<tr>
<td>Uncoordinated Solar-Thermal</td>
</tr>
<tr>
<td>Coordinated Solar-Thermal</td>
</tr>
<tr>
<td>Coordination gain</td>
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<tr>
<td>% gain</td>
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<table>
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<tr>
<th>Table 2: Unit commitments of uncoordinated thermal bidding</th>
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<tr>
<td>Unit</td>
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<tr>
<td>------</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>3</td>
</tr>
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</table>

6.2 Coordination Including V2G Services

In this case, the V2G services are included in the optimization problem with $\beta = 0$. Table 4, shows that the expected profit is further increased by 1.2 % due to EV charging coordination with solar-thermal bidding strategy. Figure 2, shows the reserves capacities and EV charging profile. It demonstrates that the maximum amount of balancing capacity is always scheduled. Balancing services are provided at lesser cost by scheduling POP. It can be observe that the POP is scheduled at higher average values where solar (stochastic) power is available. From figure 2 it can be depict that MnAP = POP and POP + MxAP = MP.

6.3 Risk Averse Attitude

Figure 3, shows the reserve capacities and optimal POP scheduling for risk-averse case with $\beta = 0.4$. Comparing it with figure 2 shows the average level of scheduled POP or regulation up capacity is higher in risk-averse case. The reason for keeping regulation up capacity higher is to avoid under generation penalties that are usually higher than over-generation penalties.

<table>
<thead>
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<th>Table 4: Coordination benefit due to V2G</th>
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<tr>
<td>Cases</td>
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<tr>
<td>Coordinated Solar-Thermal with EV opportunistic charging</td>
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<tr>
<td>Coordinated Solar-Thermal in coordination with V2G</td>
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<tr>
<td>Coordination gain</td>
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<tr>
<td>% gain</td>
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7. CONCLUSION

In this work, solar-thermal coordinated trading are proposed in coordination with unidirectional V2G services. Firstly, the strategy of coordinating solar with thermal energy is developed with the objective of maximizing the total expected profit of the utility while considering uncertainties in market prices, load and solar power output. It is shown that coordinated bidding of the energy mix can increase the expected profit. It is also shown that the thermal units are committed more often in coordinated case to avoid imbalance penalties and to maximize the expected profit. Secondly, provision of V2G services in coordination with energy trading is also described. The case of a utility is considered with mixed energy generation that serves a load with high penetration of EVs. The results show that the expected profits are increased. The risk analysis carried out shows that coordination also helps to improve CVaR which allows the utility to participate in the market more aggressively and at a lower risk.

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