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Operations Optimization of Hybrid Energy Systems under Variable Markets

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***Abstract*—Hybrid energy systems (HES) have been proposed to be an important element to enable increasing penetration of clean energy. This paper investigates the operations flexibility of HES, and develops a methodology for operations optimization to maximize its economic value based on predicted renewable generation and market information. The proposed operations optimizer allows systematic control of energy conversion for maximal economic value, and is illustrated by numerical results.**

***Index Terms*—Hybrid energy systems, renewable, operations optimization.**

I. INTRODUCTION

Hybrid energy systems (HES) have been proposed to be an important element to enable higher penetration of clean energy generation, [1]–[7]. Prior works suggest that HES can be operated under flexible operations schedules to accommodate the variability introduced from renewable generation and power markets, [4]–[6]. Such flexibility enables the participation of HES in several markets including wholesale ancillary service [4]. HES take energy inputs from Controllable Energy Resources (CER, e.g., nuclear station), Variable Energy Resources (VER, e.g., wind farm), and Energy Storage Elements (ESE, e.g., electrical battery). HES typically include one or more Alternative Production Plants (APP) besides a Power Cycle (PC). These APP allow the repurposing of energy for non-electricity commodity production. HES interrelate with feedstock markets for the procurement of feedstock material, with power market for the sale of electricity and ancillary service, and with commodity market for the sale of commodities (alternative energy output). Furthermore, each market in turn includes several forward and spot markets. While a forward market is a financial market by which contracts for future delivery of product are cleared, a spot market is such that commodities are traded for immediate delivery [8].

Optimization on HES has been investigated in the literature, e.g., [3], [9], [10]. The objective of the proposed operations optimizer is to compute operations schedule among HES constituents for optimal economic performance. Such operations optimizer collects predicted information on VER generation and various market information, and updates the operations of the given HES through low-level controllers according to the computed optimized schedule.

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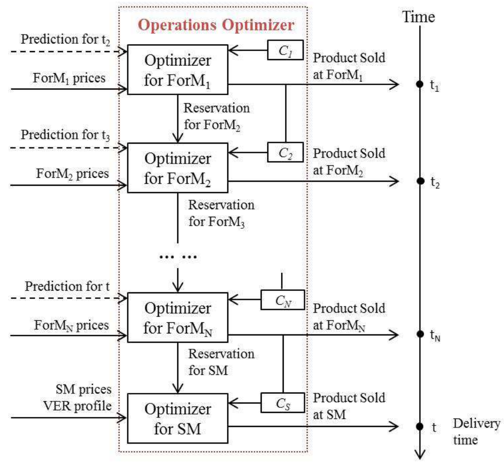

Fig. 1. Computational flow of the proposed operations optimizer.

The computational flow of the proposed operations optimizer is shown in Fig. 1. For each delivery time t (at which all the products sold in each forward market [ForM] and spot market [SM] need to be delivered), N forward markets and one spot market are considered. The optimization starts at ForM_1 by computing the optimal strategy between selling products at ForM_1 and holding resources for the next available market, based on current prices and prediction of VER generation and future prices. The optimization problem at ForM_1 is constrained by C_1 resulted from system dynamics and available resources. Such optimization repeats for each ForM and then also for SM. Similar to the case of ForM, the optimization for SM is based on the SM prices and VER profile, and is constrained by C_S. At each delivery time t, the optimal operations schedule is computed by adding the optimal strategies resulted from each forward and spot market.

The contributions of this work are as follows: (1) a framework to economically optimize operations of HES under variable renewable generations and market volatility; (2) evaluate, under the proposed operations optimizer, the economic viability of HES.

II. NOTATIONS AND PRELIMINARIES

HES configuration: In general, HES may consist of multiple generation units including CER and VER, and multiple energy conversion units besides Power Cycle. Without loss of generality, HES considered here include one CER (denoted as Primary Heat Generation or PHG), one VER (modeled

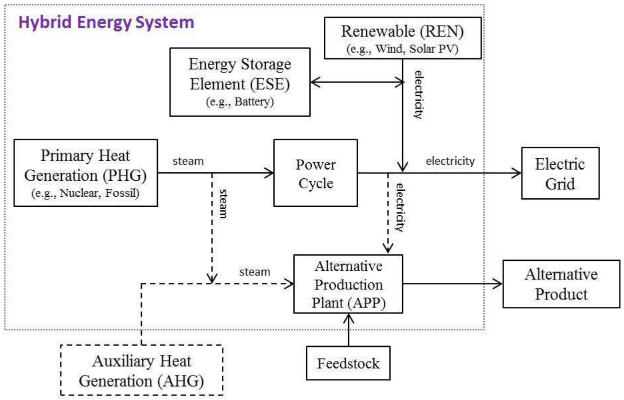

Fig. 2. Architectural topology of considered HES in this work.

as renewable energy input and denoted as REN), and one APP, as shown in Fig. 2. Note that APP may require process steam and/or electricity for production, and an Auxiliary Heat Generation (AHG) may be used to generate on-demand steam if required by APP.

Optimization methodology: The standard form of a constrained optimization problem is given as follows:

$$\begin{array}{lll} \text{minimize} & f(x) & \\ \text{subject to} & g_i(x) \leq 0 & i = 1, \ldots, k \\ & h_i(x) = 0 & i = 1, \ldots, p \end{array}$$

where $f(x) : \mathbb{R}^n \rightarrow \mathbb{R}$ is the objective function to be minimized over decision variables x, and $g_i(x)$ and $h_i(x)$ are the set of inequality and equality constraints, respectively. To solve this general optimization problem, one needs to design an algorithm that iterates the values of the decision variables and terminates only when certain conditions regarding the values of the objective function and constraints are met (e.g., Karush-Kuhn-Tucker [KKT] conditions [11]). Numerous algorithms, including gradient-based and gradient-free methods have been developed and applied to a wide variety of optimization problems, e.g., [12] and [13]. In this paper, the interior-point method [14] that aims at solving linear and nonlinear convex optimization problems is chosen as the optimizaton algorithm.

Electric power market: A common practice in deregulated power market is the two-settlement process consisting of day-ahead market and real-time market. Day-ahead market (DAM) is a forward market in which offers and bids on electricity and ancillary service are made for each hour of the next day. DAM is cleared and closed before the delivery date. On the other hand, to balance the difference between commitment in DAM and the actual demand, real-time market (RTM, a spot market) allows the transactions on electricity and ancillary service during the course of the operating day, with delivery time near "real-time" (e.g., within one hour). The delivery period can vary from five minutes to half hour depending on market designs. In this work an RTM with delivery period of 15 minutes is investigated.

III. Economic Functions

A. Economic figures of merit (FOM)

The economic FOMs considered here include net present value (NPV), payback period, and internal rate of return (IRR). In particular, NPV is defined as follows [15]:

$$NPV = \sum_{k=0}^{N} \frac{FCFF_{R,k}}{(1+r_R)^k}, \tag{1}$$

where N is the years of operations of HES, r_R denotes the discount rate (assumed to be 5%) used in computing weighted average cost of capital (WACC), and $FCFF_{R,k}$ is the real discounted Free Cash Flow to Firm for year k, defined as:

$$\begin{aligned} FCFF_{R,k} = (R_k - C_{O\&M,k} - DA_k(1+i)^{-k})(1-\sigma) \\ + DA_k(1+i)^{-k} - C_{ghg,k} - CAPEX_k, \end{aligned} \tag{2}$$

where σ is tax rate, and i is inflation rate (assumed to be 3%). $CAPEX_k$ (capital expense) only occurs when $k = 0$, i.e., year 0, given by $CAPEX_0 = C_{cap}$, and $CAPEX_k = 0$ for all $k > 0$. The capital cost C_{cap}, operations and maintenance (O&M) cost $C_{O\&M,k}$, cost for greenhouse gas (GHG) emission $C_{ghg,k}$, and revenue R_k, for year k, are given by equations (3), (4), (6), and (7), respectively, in the following sections. Depreciation and amortization for year k for tax deduction under Modified Accelerated Cost Recovery Systems (MACRS), i.e., DA_k in (2), is calculated by $DA_k = \rho_{da,k} C_{cap}$, where $\rho_{da,k}$ is the DA rates[1] at year k.

Payback period, or payback time, is defined as the years of operations such that NPV equals 0 [17]. Finally, for a fixed N years of operations, the IRR is defined as the value of the discount rate r_R such that NPV equals 0 [18].

B. Economic functions for cost and revenue

Economic functions introduced here are necessary for computations of above economic FOMs. For simplicity of presentation, we only consider spot market for feedstock and alternative product, and one forward market and one spot market for electricity. Note that while some variables are varying with respect to time t, they are denoted without subscript t when there is no confusion.

a) Capital cost: The capital cost C_{cap} associated with building HES includes costs relevant to PHG (including PC), AHG (optional), APP, REN, and ESE as follows:

$$C_{cap} = C_{phg} + C_{ahg} + C_{app} + C_{ren} + C_{ese}. \tag{3}$$

The capital cost for PHG (including PC) is calculated as: $C_{phg} = \alpha_{phg} \mathcal{N}_{phg}$, where α_{phg} is the capital cost per unit of installed capacity and $\mathcal{N}_{phg}$ denotes the installed capacity of PHG. Similar equations are formulated for computing C_{ahg}, C_{app}, C_{ren}, and C_{ese} by replacing the subscript "phg" with ahg, app, ren, and ese, respectively.

[1] $\rho_{da,k}$ for $k \leq 16$, i.e., the first 16 years, are 5.00%, 9.50% , 8.55%, 7.70%, 6.93%, 6.23%, 5.90%, 5.90%, 5.91%, 5.90%, 5.91%, 5.90%, 5.91%, 5.90%, 5.91%, 2.95%, respectively, and 0% afterwards [16].

b) Operations and maintenance cost: The O&M cost $C_{O\&M,k}$ for year k can be further divided into fixed O&M cost, $O\&M_f$, and variable O&M cost, $O\&M_v$, i.e.,

$$C_{O\&M,k} = O\&M_f + O\&M_v. \tag{4}$$

Note that $O\&M_f$ includes O&M cost that is relatively constant with respect to operations, while $O\&M_v$ essentially corresponds to the cost of fuel and other feedstock. Similarly to capital cost, $O\&M_f$ and $O\&M_v$ are given as following:

$$\begin{aligned} O\&M_f &= O\&M_{f\_phg} + O\&M_{f\_ahg} + O\&M_{f\_app} \\ &\quad + O\&M_{f\_ren} + O\&M_{f\_ese} \\ O\&M_v &= O\&M_{v\_ahg} + O\&M_{v\_app}, \end{aligned} \tag{5}$$

with $O\&M_{f\_ahg}$ and $O\&M_{v\_ahg}$ being optional (depending on specific HES configuration). The fixed O&M cost for PHG is calculated as: $O\&M_{f\_phg} = \beta_{f\_phg} C_{phg}$, where β_{f_phg} is used to indicate that the (annual) fixed O&M cost for operating PHG is a fraction of its capital cost. Similar equations are formulated for computing $O\&M_{f\_ahg}$, $O\&M_{f\_app}$, $O\&M_{f\_ren}$, and $O\&M_{f\_ese}$ by replacing the subscript "*phg*" with ahg, app, ren, and ese, respectively. The variable O&M cost for APP is calculated by:

$$O\&M_{v\_app} = \sum_{n=1}^{N_{app}} \int_0^T \beta_{v\_app,n} M_{v\_app,n} dt,$$

where T is the considered time period (e.g., a year), $M_{v\_app,n}$ and $\beta_{v\_app,n}$ are the consuming rate and price of the nth feedstock, respectively. Similar equation for AHG is formulated by replacing the subscript "app" with "ahg".

c) Greenhouse gas emission cost: Since CO_2 is the dominant GHG, this cost is essentially equal to the CO_2 cost, computed as follows:

$$C_{ghg,k} = \int_0^T \beta_{co_2} M_{co_2} dt, \tag{6}$$

where β_{co_2} is the taxation rate over CO_2 and M_{co_2} is the combined CO_2 emission rate by all components within HES.

d) Revenues from sale of electricity and commodity: The revenue R_k for year k can be computed as

$$R_k = R_{da,e} + R_{da,as} + R_{rt} + R_{app}, \tag{7}$$

where $R_{da,e}$, $R_{da,as}$, R_{rt} and R_{app} represent the revenues from sale of electrical energy in DAM, sale of ancillary services in DAM, sale of electrical energy in RTM, and sale of alternative product in commodity market. $R_{da,e}$ can be computed by $R_{da,e} = \int_0^T \pi_{da,e} P_{da,e} dt$, where $\pi_{da,e}$ is the price of electrical energy in DAM and $P_{da,e}$ is the amount of power sold in DAM, both potentially varying with time. Similar equations are formulated for computing $R_{da,as}$, R_{rt}, and R_{app} by replacing the subscript "da, e" with "da, as", "rt", and "app", respectively. When the ancillary service is called for, the energy delivered as ancillary service will be remunerated at the real-time price π_{rt}. This "hidden" revenue is implicitly included in $R_{da,as}$ as shown in Section IV.

IV. Economic Optimization of Operations

It is not hard to see that, maximizing the NPV, minimizing the payback period T_{pb}, and maximizing the IRR, are all equivalent to maximizing the $FCFF_{R,k}$ defined in (2) for each year k (assuming system design is fixed). By dropping from (2) the terms that are constant with respect to operations, which include $O\&M_f$, $CAPEX_k$, and terms related to DA_k, the objective function for operations optimization is thus formulated as:

$$J = (R_k - O\&M_v)(1 - \sigma) - C_{ghg,k}. \tag{8}$$

In the following sections, two operations optimizers are introduced, one for DAM and one for RTM. The optimizer for DAM, denoted as DAO (day-ahead optimizer), maximizes (8) by computing the optimal amounts of energy and ancillary service capacity sold in DAM, as well as the amount of energy held to participate in RTM. It is assumed that the price in RTM and the renewable generation available at the delivery time need to be predicted by DAO, while all other price information are well known. On the other hand, the optimizer for RTM, denoted as RTO (real-time optimizer), maximizes (8) by computing the optimal amount of energy sold in RTM, based on the results of DAO. It is assumed that both price in RTM and renewable generation are known by RTO.

A. Optimization for day-ahead market

For each hour interval, the objective function for DAO is given as, by expanding (8) using (5), (6), and (7),

$$\begin{aligned} J_{da} &= (1 - \sigma) \int_0^{\Delta T} [\pi_{da,e} P_{da,e} + (\pi_{da,as} + p_{as} \widetilde{\pi}_{rt}) P_{da,as} \\ &\quad + \widetilde{\pi}_{rt} P_{da,rt} + \pi_{app} \widetilde{M}_{app} - \sum_{n=1}^{N_{app}} \beta_{v\_app,n} \widetilde{M}_{v\_app,n} \\ &\quad - \sum_{n=1}^{N_{ahg}} \beta_{v\_ahg,n} \widetilde{M}_{v\_ahg,n}] dt - \int_0^{\Delta T} \beta_{co_2} \widetilde{M}_{co_2} dt, \end{aligned} \tag{9}$$

where ΔT is one hour interval, $P_{da,rt}$ is the amount of power held to participate in real-time market, and notation $\widetilde{\cdot}$ means the prediction of corresponding variables. The decision variables considered by DAM are $P_{da,e}$, $P_{da,as}$, $P_{da,rt}$, $\widetilde{M}_{app}$, $\widetilde{M}_{v\_app,n}$, $n = 1, \ldots, N_{app}$, $\widetilde{M}_{v\_ahg,n}$, $n = 1, \ldots, N_{ahg}$. Constraints over decision variables are given as follows,

$$\widetilde{P}_{app} + P_{da,e} + P_{da,rt} = P_{phg} + \widetilde{P}_{ren} \tag{10}$$

$$P_{app}^L \le \widetilde{P}_{app} \le P_{app}^U \tag{11}$$

$$P_{da,as} \le \widetilde{P}_{app} - P_{app}^L \tag{12}$$

$$\begin{aligned} & f_i(P_{da,e}, P_{da,as}, P_{da,rt}, \widetilde{M}_{v\_app,1}, \ldots, \widetilde{M}_{v\_app,N_{app}} \\ & \quad \widetilde{M}_{v\_ahg,1}, \ldots, \widetilde{M}_{v\_ahg,N_{ahg}}, \widetilde{M}_{app}, \widetilde{M}_{co_2}) = 0. \end{aligned} \tag{13}$$

Combining (10) and (11) gives $P_{app}^L \le P_{phg} + \widetilde{P}_{ren} - P_{da,e} - P_{da,rt} \le P_{app}^U$, or equivalently

$$P_{phg} + \widetilde{P}_{ren} - P_{app}^U \le P_{da,e} + P_{da,rt} \le P_{phg} + \widetilde{P}_{ren} - P_{app}^L. \tag{14}$$

Similarly, combining (10) and (12) gives $P_{da,as} \leq P_{phg} + \widetilde{P}_{ren} - P_{da,e} - P_{da,rt} - P_{app}^L$, or equivalently

$$P_{da,e} + P_{da,as} + P_{da,rt} \leq P_{phg} + \widetilde{P}_{ren} - P_{app}^L. \quad (15)$$

To ensure that the above constraints (14) and (15) are satisfied within the entire period of each hour, we have:

$$P_{phg} + \widetilde{P}_{ren}^U - P_{app}^U \leq P_{da,e} + P_{da,rt} \leq P_{phg} + \widetilde{P}_{ren}^L - P_{app}^L \quad (16)$$

$$P_{da,e} + P_{da,as} + P_{da,rt} \leq P_{phg} + \widetilde{P}_{ren}^L - P_{app}^L, \quad (17)$$

where $\widetilde{P}_{ren}^U$ and $\widetilde{P}_{ren}^L$ are the maximum and minimum of the predicted renewable generation within the hour. Furthermore, it is also assumed that the capacity sold as ancillary service and the energy held for real-time market cannot exceed certain limits, denoted as $P_{da,as}^U$ and $P_{da,rt}^U$, respectively. Therefore,

$$0 \leq P_{da,as} \leq P_{da,as}^U \quad (18)$$

$$0 \leq P_{da,rt} \leq P_{da,rt}^U. \quad (19)$$

Finally, we have

$$P_{da,e} \geq 0. \quad (20)$$

In summary, the optimization problem for DAM is formulated as:

$$\begin{aligned} &\text{maximize} && J_{da} \text{ as in } (9) \\ &\text{subject to} && (10),\ (13),\ (16)-(20) \end{aligned}$$

B. Optimization for real-time market

For each quarter hour interval, the objective function for RTO is given by expanding (8) using (5), (6), and (7), as:

$$\begin{aligned} J_{rt} = (1-\sigma)\int_0^{\Delta T} &[\pi_{da,e}P_{da,e} + (\pi_{da,as} + p_{as}\pi_{rt})P_{da,as} \\ &+ \pi_{rt}P_{rt} + \pi_{app}M_{app} - \sum_{n=1}^{N_{app}} \beta_{v\_app,n}M_{v\_app,n} \\ &- \sum_{n=1}^{N_{ahg}} \beta_{v\_ahg,n}M_{v\_ahg,n}]dt - \int_0^{\Delta T} \beta_{co_2}M_{co_2}dt, \quad (21) \end{aligned}$$

where, with a slight abuse of notation, ΔT is a quarter hour interval, and P_{rt} is the amount of electricity sold in RTM. The decision variables considered by RTO are P_{rt}, M_{app}, $M_{v\_app,n}$, $n = 1, \ldots, N_{app}$, $M_{v\_ahg,n}$, $n = 1, \ldots, N_{ahg}$, and M_{ahg,co_2}. Since in this case DAM has been closed and all transactions are cleared, $P_{da,e}$ and $P_{da,as}$ are no longer variables and their values throughout the course of the day are fixed by DAO. Likewise, constraints can be reformulated as follows:

$$P_{app} + P_{da,e} + P_{rt} = P_{phg} + P_{ren} \quad (22)$$

$$P_{app}^L \leq P_{app} \leq P_{app}^U \quad (23)$$

$$P_{da,as} \leq P_{app} - P_{app}^L \quad (24)$$

$$\begin{aligned} f_i(&P_{da,e}, P_{da,as}, P_{da,rt}, M_{v\_app,1}, \ldots, M_{v\_app,N_{app}} \\ &M_{v\_ahg,1}, \ldots, M_{v\_ahg,N_{ahg}}, M_{app}, M_{co_2}) = 0. \quad (25) \end{aligned}$$

Combining (22) and (23) gives $P_{app}^L \leq P_{phg} + P_{ren} - P_{da,e} - P_{rt} \leq P_{app}^U$, or equivalently

$$P_{phg}+P_{ren}-P_{da,e}-P_{app}^U \leq P_{rt} \leq P_{phg}+P_{ren}-P_{da,e}-P_{app}^L. \quad (26)$$

Similarly, combining (22) and (24) gives $P_{da,as} \leq P_{phg} + P_{ren} - P_{da,e} - P_{rt} - P_{app}^L$, or equivalently

$$P_{rt} \leq P_{phg} + P_{ren} - P_{da,e} - P_{da,as} - P_{app}^L. \quad (27)$$

To ensure that the above constraints (26) and (27) are held within the entire period of each quarter hour, we have:

$$P_{phg}+P_{ren}^U-P_{da,e}-P_{app}^U \leq P_{rt} \leq P_{phg}+P_{ren}^L-P_{da,e}-P_{app}^L \quad (28)$$

$$P_{rt} \leq P_{phg} + P_{ren}^L - P_{da,e} - P_{da,as} - P_{app}^L, \quad (29)$$

where P_{ren}^U and P_{ren}^L are the maximum and minimum of the renewable generation within that quarter hour. Furthermore,

$$P_{rt} \geq 0. \quad (30)$$

When the real-time price of electricity is non-positive, none of the electricity should be sold in RTM. Hence, in this case

$$P_{rt} = 0. \quad (31)$$

In summary, the optimization problem for RTM is formulated as:

$$\begin{aligned} &\text{maximize} && J_{rt} \text{ as in } (21) \\ &\text{subject to} && (22),\ (25),\ (28)-(30) \\ & && (31) \text{ if } \pi_{rt} \leq 0 \end{aligned}$$

Remark 1: To check the feasibility of this optimization problem, define

$$\begin{aligned} B_1 &:= P_{phg} + P_{ren}^U - P_{da,e} - P_{app}^U \\ B_2 &:= P_{phg} + P_{ren}^L - P_{da,e} - P_{app}^L \\ B_3 &:= P_{phg} + P_{ren}^L - P_{da,e} - P_{da,as} - P_{app}^L. \end{aligned}$$

It can be verified that $B_2 \geq B_1$ and $B_2 \geq B_3$, so the feasible condition for the above optimization problem is given by:

- When $\pi_{rt} > 0$, then it is feasible only if $\min(B_2, B_3) \geq \max(0, B_1)$, which in turn requires $B_3 \geq \max(0, B_1)$.
- When $\pi_{rt} \leq 0$, then it is feasible only if $\min(0, B_2, B_3) \geq \max(0, B_1)$, requiring $B_1 \leq 0 \leq B_3$.

When it is not feasible, any operations in RTM will violate either (28) or (29). In this case, a standby ESE is charged or discharged to ensure energy balance within HES (i.e., the feasibility of above optimization problem). ■

V. Numerical Results and Discussions

This section presents numerical results to illustrate the proposed operations optimizer. A specific HES configuration taken from [4], [5], termed as HES_FEL (hybrid energy system with flexible electrical load), is utilized here for discussion.

A. Hybrid Energy System with Flexible Electrical Load

HES_FEL includes the following primary components:

- PHG: a nuclear reactor and a steam generator;
- PC: a Rankine cycle consisting of steam generator, turbines, electric generator, condenser, feedwater pumps and heaters, producing electricity up to 180 MW;
- REN: a solar photovoltaic (PV) station with nominal capability of up to 30 MW;
- ESE: two electrical batteries, with storage capacities of 52.7 MWh and 10 MWh, respectively;
- AHG: none;
- APP: a reverse osmosis desalination plant (RODP) able to utilize up to 45 MW electricity and convert saline or brackish water into fresh water and brine;
- sufficient saline or brackish water and an electric grid connected to HES_FTL at a point of common coupling.

In HES_FEL, an RODP is used as APP, requiring electricity as its energy input (no AHG is present). The production rate of RODP is varying between $P_{app}^L = 15$ MW and $P_{app}^U = 45$ MW, as dictated by the operations optimizer. The variable O&M cost of RODP is presented by a lump-sum variable cost, i.e., $N_{app} = 1$, with $\beta_{v\_app,1}$ being a lump-sum coefficient. The equality constraints (13) can be rewritten as[2]:

$$\begin{aligned} M_{app} &= k_0 + k_1 P_{app} + k_2 P_{app}^2 \\ M_{co_2} &= 0. \end{aligned} \tag{32}$$

B. Simulation setup

The prices for electricity and ancillary service in DAM, and price of electricity in RTM, all provided by ERCOT[3] (Electric Reliability Council of Texas), are used for $\pi_{da,e}$, $\pi_{da,as}$ and π_{rt}, respectively, as shown in Fig. 3(a) for a selected period of 14 days. The price of water is based on the monthly residential price in Phoenix, Arizona[4], which is scaled such that the average of the time series is \$0.6 per cubic meters, corresponding to the cost for purchasing groundwater or surface water in Arizona [19], as shown in Fig. 3(b).

The predicted and actual renewable generation are synthesized based on reference time series (denoted as ref_r) computed from solar irradiation measurement data[5]. For a fixed prediction error rate p_r, the time series of predicted renewable generation for DAO (denoted as $pred_r$) is synthesized so that it is uniformly distributed within range $(1 \pm p_r)ref_r$. The time series of actual renewable generation (denoted as act_r) is synthesized so that, with probability of 0.9, it is uniformly distributed within range $(1 \pm p_r)ref_r$ and, with probability of 0.1, it is uniformly distributed within range $([1+p_r)ref_r,\ (1+2p_r)ref_r] \cup [(1-2p_r)ref_r,\ (1-p_r)ref_r]$. The prediction of real-time electricity price for DAO is carried out in a similar fashion. For a fixed prediction error rate p_m, the time series of predicted real-time electricity price (denoted as $pred_m$) is synthesized so that it is uniformly distributed with range $(1 \pm p_m)ref_m$, where the reference time series ref_m is shown in Fig. 3(a). The time series of actual price (denoted as act_m) is synthesized by $act_m = ref_m$. Table I lists all the parameter values assumed in the simulations.

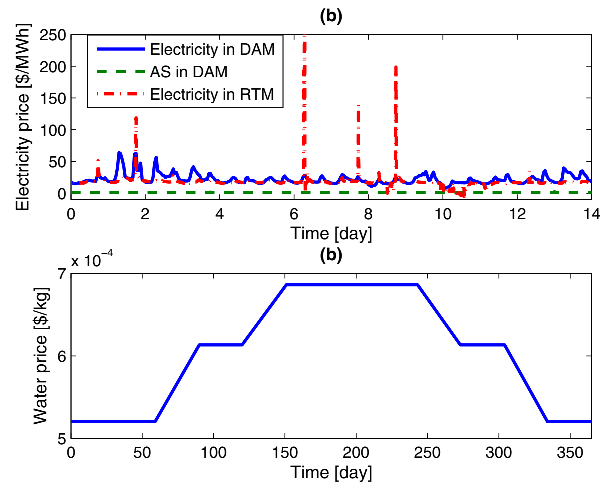

Fig. 3. (a) Prices for electricity and ancillary service for selected 14 days; (b) Water price for a whole year.

C. Numerical results

Fig. 4 presents the optimization results for selected 14 days, assuming perfect prediction, where Fig. 4(a) shows the optimal electricity sold in DAM, ancillary service sold in DAM, and electricity sold in RTM, respectively, and Fig. 4(b) shows the total electricity delivered to the electric grid and net load (electrical generation delivered to the electric grid by PHG). Note that the scenarios in which committed ancillary service is called for are also simulated and included in Fig. 4(b).

To demonstrate the advantage of proposed operations optimizer, a simulation is conducted with constant operations (i.e., $P_{da,e}$ is fixed at 165 MW, and both $P_{da,as}$ and P_{rt} areassumed to be 0). Table II shows that $FCFF_{R,1}$ with operations optimizer increases by 82.38% compared to that of constant operations mode. Fig. 5 plots NPV as a function of operations time. The payback period is about 15.29 years, and the IRR for 30 years of operations is 8.2%, both under the optimized case.

Furthermore, Fig. 6 shows that the decrease of $FCFF_{R,1}$ resulted by imperfect prediction monotonically increases as renewable prediction error (left) or real-time electricity price prediction error (right) increases, as expected.

[2]The values for k_0, k_1, and k_2 in (32) are determined by simulations of HES_FEL modeling in Modelica, and are given as $k_0 = 301.77$, $k_1 = 442.20$, and $k_3 = -2.16$.

[3]Downloaded from http://www.ercot.com/mktinfo/prices/index.html on February 4, 2015. The time series is scaled by 0.75 to reflect the conservativeness of HES in bidding.

[4]Downloaded from https://www.phoenix.gov/waterservices/customerservices/rateinfo on February 5, 2015.

[5]Downloaded from http://www.nrel.gov/midc/ssrp/ on November 21, 2014, provided by Southwest Solar Research Park dataset maintained by NREL (National Renewable Energy Laboratory).

TABLE I
PARAMETER VALUES USED SIMULATION

Component	Parameter	Value	Unit	Ref.
Nuclear & Power Cycle	α_{phg}	4718	\$ kW^{-1}	[20], [21]
	β_{f_phg}	5.2	%	[22]
	$\mathcal{N}_{phg}$	180,000	kW	[5]
PV Station	α_{ren}	5385.98	\$ kW^{-1}	[23]
	β_{f_ren}	1	%	[24]
	$\mathcal{N}_{ren}$	30,000	kW	[5]
Storage	α_{ese}	81.42	\$ kWh^{-1}	[2]
	β_{f_ese}	3	%	[2]
	$\mathcal{N}_{ese,1}$	52,700	kWh	[5]
	$\mathcal{N}_{ese,2}$	10,000	kWh	Sec. V-A
RO Desalination Plant	α_{app}	32,076.21	\$ kg^{-1}s	[25]
	β_{f_app}	15	%	[25]
	$\beta_{v\_app,1}$	6.6e^{-5}	\$ kg^{-1}	[26]
	$\mathcal{N}_{app}$	15614	kgs^{-1}	[5]
	π_{app}		\$ kg^{-1}	Fig. 3
	k_0	301.77	kgs^{-1}	footnote[2]
	k_1	442.20	kgs^{-1}MW^{-1}	footnote[2]
	k_2	-2.16	kgs^{-1}MW^{-2}	footnote[2]
Electricity	$\pi_{da,e}$		\$ MWh^{-1}	Fig. 3
	$\pi_{da,as}$		\$ MWh^{-1}	Fig. 3
	π_{rt}		\$ MWh^{-1}	Fig. 3
	p_{as}	0.3	%	[27]
Inflation Rate	i	3	%	Sec. III
Discount Rate (WACC)	r_R	5	%	Sec. III
DA Rates	$\rho_{da,k}$	footnote[1]	%	[16]
Tax Rate	σ	40	%	[28], [29]

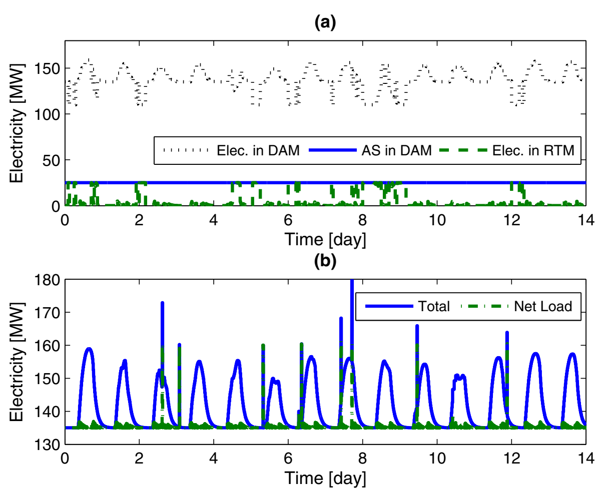

Fig. 4. Optimization result for selected 14 days (HES_FEL) assuming perfect prediction: (a) Optimal electricity and ancillary service sold in each market; (b) Total electrical generation and net load to PHG.

VI. Conclusions and Ongoing Efforts

This paper proposed an operations optimizer for hybrid energy systems (HES) to maximize their economic performance based on predicted renewable generation and market information. The proposed operations optimizer allows systematic control of energy conversion for maximal economic value, hence improving the economic attractiveness of HES. Simulation results of a specific HES configuration demonstrated the advantage of the proposed operations optimizer. Future efforts include: (1) operations optimization under even more complex market dynamics; (2) model predictive control for operations to optimize combined technical and economic performance.

TABLE II
REAL DISCOUNTED FCFF FOR THE FIRST YEAR OF OPERATIONS

Economic value	Optimal mode	Constant mode	Gain
Revenue - Electricity	\$38,256,342	\$41,665,881	-8.18%
Revenue - Fresh water	\$301,385,549	\$178,461,804	68.88%
Cost - RODP	(\$32,775,861)	(\$19,360,846)	69.29%
FCFF	\$140,938,245	\$77,278,730	82.38%

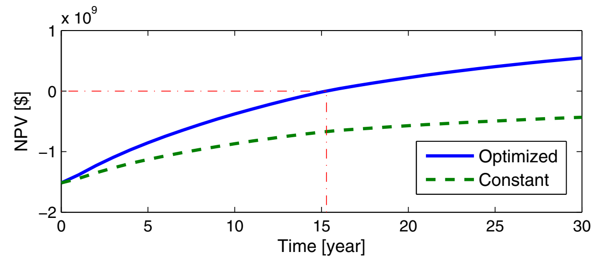

Fig. 5. NPV as a function of operations time, assuming perfect prediction.

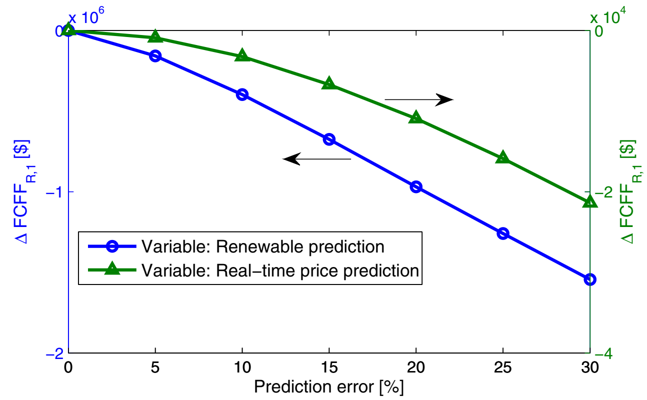

Fig. 6. Deviation of first year FCFF as a function of prediction errors.

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