Economic Cost-Benefit Analysis for Power System Operations with Environmental Considerations

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***Abstract*—This paper presents a model aimed at evaluating the effects of integrating Renewable Energy Sources (RES) in the electricity system, from the perspective of a system operator, taking into account the cost of Carbon Dioxide ($C0_2$) emissions. The model is especially suited to analyze the interactions of energy storage systems (ESS) with conventional generation sources, in the framework of reliable operation ($n-1$). One of the most important consequences of high levels of RES in the network is the variability induced on the existing generation fleet, and the wear-and-tear derived from ramping conventional units to counteract the changes in RES output. Our Security-Constrained Optimal Power Flow (SC-OPF) optimizes the injection into the network, including the cost of changes between periods for a given horizon. The results show that the main benefits derived from ESS are the reduction in the provision of ancillary services from conventional generation sources. These services are instead provided by ESS units. This is an important additional revenue stream for storage system owners, especially in the face of the cost of capital of these resources.**

***Index Terms*—Ramping costs, Energy Storage Systems, Renewable Generation**

I. Introduction

The constant balancing between supply and demand in the electricity sector make the operation of the system a challenge. This challenge becomes more difficult, as the uncertainty in the system increases with the increased penetration of renewable energy sources (RES) [1]. The purpose of this paper is to present a new formulation of a hybrid stochastic-robust optimization for look-ahead, security-constrained optimization of the operation of power systems. It is a form of stochastic optimization that is tractable in spite of the high dimensionality that results from taking into account the temporally linked probability distributions of stochastic variables such as wind generation. We also include reserve needs, contingency risks, storage device operation, ramping costs and demand functions [2]. The inter-temporal trade-offs and transversality of energy storage systems are a focus of the formulation.

This paper is organized as follows. Section II discusses the previous literature and the background information to this problem, and introduces our model for operations. Section III includes a set of considerations for the calibration of the model. Section IV presents an application to a reduced network, taking into accounts the inputs necessary, and summarizes the application to a case study. Concluding remarks are offered in section V

II. Background and Theoretical Framework

The framework presented in this section has two purposes: first, it relates our model to past work, while showing its distinctive advantages in dealing with stochastic sources of noise.

Second, it shows a simplified objective function, providing intuitive explanation of the tradeoffs occurring. Due to space constraints we provide a brief overview of the model and do not include the full model here.

The electricity system is dispatched minimizing the total cost of delivering energy, subject to the technical and demand constraints for an Optimal Power Flow (OPF) [3]. As part of this optimization, both continuous and discrete variables are included, representing the cost of fuel and the startup and shutdown costs, combining the OPF and Unit Commitment (UC) problems [4].

The recent literature in stochastic programming applied to the electricity system studies the optimization performed by the System Operator (SO), with inclusion of uncertainty as ex-post consideration [5], with estimation of the scenarios causing disturbances [6], [7], [8] or using robust [9] approaches. Our proposed model uses an ambiguity robust approach [10]. This is an intermediate approach between a stochastic and a robust optimization that has been proven in obtaining computationally efficient solutions avoiding problems with non economical feasibility. This can be generally expressed as

$$\min_{x} \left(\max_{s} \mathbb{E}_s[G(x,s,\epsilon)] \right) \text{ Subject to } x \in \mathbb{X} \tag{1}$$

Where $\mathbb{E}_s$ is the expectation with respect to a random ϵ with distribution s, the variable x depends on ϵ, $\mathbb{X}$ is a convex set of feasible solutions and $G(\cdot)$ is a convex cost function in x. Our framework extends on a security constrained-OPF, with emphasis on security over a high probability set of scenarios.

The schematics of the modeling are illustrated in figure 1, showing two intra-temporal high probability scenarios, each one tied to two low probability scenarios ("contingency OPF scenario") and 3 time periods. This model is implemented based on MATPOWER's extensible OPF architecture [11].

In our model, the SO seeks to maximize the total social welfare, with the different components of the objective function including:

1) The cost of energy delivered
2) The cost of re-dispatching the system (e.g. deviations from contracts)
3) The benefit that consumers receive, having all their load serviced (no load shedding cost)

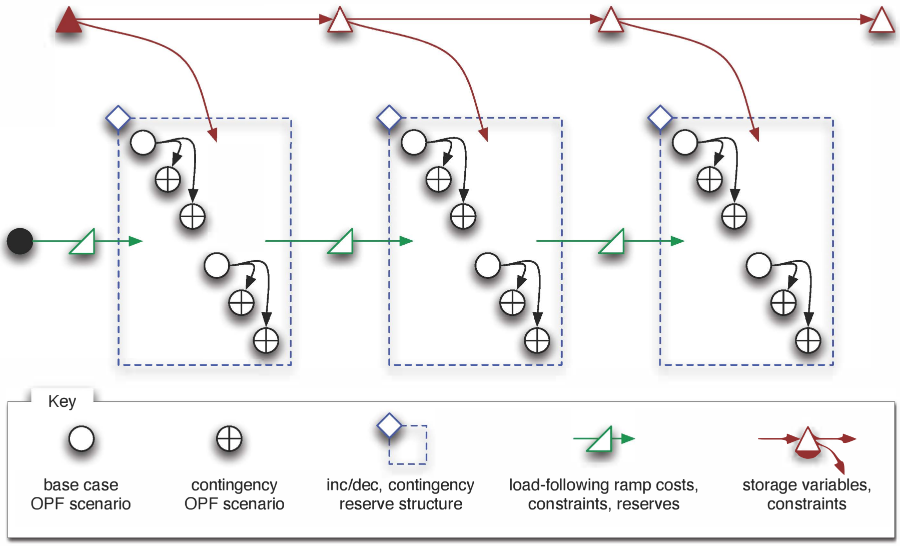

Fig. 1. Schematic of the Problem Structure

4) The cost of reserves (up and down) for low probability events (e.g. contingency reserve)
5) The cost of ancillary services, for high probability events (e.g. load following reserve)
6) The cost incurred in the transitions (e.g. ramping or wear-and-tear cost)
7) The residual cost of energy left in the ESS

The main difference with our approach is the determination of the optimal amount of ancillary services (e.g. contingency reserve for low probability events, and load following reserve for high probability events) as part of the variables in the solution set [12]. This is especially important as the amount of stochastic source of generation increases [13].

A simplified version of the objective function is shown in equation (2)

$$\begin{aligned}
\min_{G_{itsk}, R_{itsk}, \mathrm{LNS}_{jtsk}} & \sum_{t\in\mathscr{T}} \sum_{s\in\mathscr{S}^t} \sum_{k\in\mathscr{K}^{ts}} \pi_{tsk} \Bigg\{ \sum_{i\in\mathscr{I}^{tsk}} \Big[C_{G_i}(G_{itsk}) + \\
& \mathrm{Inc}^{+}_{its}(G_{itsk} - G_{itc})^{+} + \mathrm{Dec}^{-}_{its}(G_{itc} - G_{itsk})^{+} \Big] + \\
& \sum_{j\in\mathscr{J}^{tsk}} \mathrm{VOLL}_j \mathrm{LNS}(G_{tsk}, R_{tsk})_{jtsk} \Bigg\} + \\
& \sum_{t\in\mathscr{T}} \rho_t \sum_{i\in\mathscr{I}^t} [C^{+}_{R_{it}}(R^{+}_{it}) + C^{-}_{R_{it}}(R^{-}_{it}) + C^{+}_{L_{it}}(L^{+}_{it}) + \\
& C^{-}_{L_{it}}(L^{-}_{it})] + \sum_{t\in\mathscr{T}} \rho_t \sum_{s_2\in\mathscr{S}^t} \sum_{s_1\in\mathscr{S}^{t-1}} \sum_{i\in\mathscr{I}^{ts_2 0}} \\
& [\mathrm{Rp}^{+}_{it}(G_{its_2} - G_{its_1})^{+} + \mathrm{Rp}^{-}_{it}(G_{its_2} - G_{its_1})^{+}] \\
& + f_s(p_{\mathrm{sc}}, p_{\mathrm{sd}})
\end{aligned} \tag{2}$$

The constraints for the problem include

- The full set of equality constraints (e.g. power balance equations)
- The full set of inequality constraints (e.g. power generation limits)
- The set of constraints for reserve, redispatch and contract deviations
- The ramping limits for low probability events
- The ramping limits for high probability events
- Minimum startup and shutdown times, and integrality constraints

Table I summarizes the variables considered in the reduced form.

Our formulation is a potential means of improving the economic efficiency of power systems, especially with large amounts of variable generation, energy storage, or both. This model therefore is the first to our knowledge to robustly estimate the capacity needed for system operations. The fact that ancillary services are endogenously determined allows for an economic valuation of the resources that provide capacity, while making sure compliance of reliably standards is maintained. It is important to note that our model assumes the system is not in a transient state. We call this model (generalized) Matpower Optimal Power Scheduler (mops).

III. Calibration

A. Stochastic Inputs and Initial Conditions

The inputs to the model include the characterization of the uncertainty in the stochastic resource (e.g. wind), and the establishment of appropriate initial conditions.

The renewable resource considered is wind energy, discretized over a set of high probability cases ('scenarios'). This information is extracted using a principal component analysis (PCA) on wind data from the National Renewable Energy Laboratory Eastern Wind Integration Study [14], to obtain 4 scenarios as shown in Figure 2.

TABLE I
DEFINITION OF VARIABLES, SIMPLIFIED FORMULATION

$\mathscr{T}$	Set of time periods considered, n_t elements indexed by t.
$\mathscr{B}$	Set of buses in the system, n_b elements.
$\mathscr{S}^t$	Set of states in the system in period t, n_s elements indexed by s.
$\mathscr{K}^{ts}$	Set of contingencies in the system in period t and state s, n_c elements indexed by k.
$\mathscr{I}^{tsk}$	Set of generators in the system in period t, state s, and contingency k, n_g elements indexed by i.
$\mathscr{J}^{tsk}$	Set of loads in the system in period t, state s, and contingency k, n_l elements indexed by j.
π_{tsk}	Probability of contingency k occurring, in state s, period t.
ρ_t	Probability of reaching period t.
G_{itsk}	Quantity of apparent power generated (MVA), active and reactive injections ($p_{itsk} + \sqrt{-1}q_{itsk}$).
G_{itc}	Optimal contracted apparent power (MVA).
V^{tsk}	Set of voltages in period t, state s and contingency k, n_b elements for each bus in the system
θ^{tsk}	Set of angles in period t, state s and contingency k, n_b elements
p_{itsk}	Active power generated (MW), 0 refers to base case(s), n_g elements.
p^c_{it}	Optimal contracted active power (MW), n_g elements.
p^+_{itsk}, p^-_{itsk}	Upward/downward deviation from active power contract quantity for unit i in post-contingency state k of state s at time t, n_g elements.
$C_G(\cdot)$	Cost of generating $(\cdot)$ MVA of apparent power.
$\text{Inc}^+_{its}(\cdot)^+$	Cost of increasing generation from contracted amount.
$\text{Dec}^-_{it}(\cdot)^+$	Cost of decreasing generation from contracted amount.
VOLL_j	Value of Lost Load, (\$).
$\text{LNS}(\cdot)_{jtsk}$	Load Not Served (MWh).
$R^+_{it} < \text{Ramp}_i$	$(\max(G_{itsk}) - G_{itc})^+$, up reserves quantity (MW) in period t.
$C^+_R(\cdot)$	Cost of providing $(\cdot)$ MW of upward reserves.
$R^-_{it} < \text{Ramp}_i$	$(G_{itc} - \min(G_{itsk}))^+$, down reserves quantity (MW).
$C^-_R(\cdot)$	Cost of providing $(\cdot)$ MW of downward reserves.
$L^+_{it} < \text{Ramp}_i$	$(\max(G_{i,t+1,s}) - \min(G_{its}))^+$, load follow up (MW) t to $t+1$.
$C^+_L(\cdot)$	Cost of providing $(\cdot)$ MW of load follow up.
$L^-_{it} < \text{Ramp}_i$	$(\max(G_{its}) - \min(G_{i,t+1,s}))^+$, load follow down (MW).
$C^-_L(\cdot)$	Cost of providing $(\cdot)$ MW of load follow down.
$\text{Rp}^+_{it}(\cdot)^+$	Cost of increasing generation from previous time period.
$\text{Rp}^-_{it}(\cdot)^+$	Cost of decreasing generation from previous time period.
$\delta^+_{it}, \delta^-_{it}$	Upward/downward load-following ramping reserves needed from unit i at time t for transition to time $t+1$.
$\delta^{\max+}_{it}, \delta^{\max-}_{it}$	Upward/downward load-following ramping reserve limits for unit i.
$f_s(p_{\text{sc}}, p_{\text{sd}})$	Value of the leftover stored energy in terminal states.

In terms of orthodox stochastic programming terminology [15], our approach 'recycles' the end nodes in every time period in order to avoid the need to track individual trajectories.

For the establishment of initial conditions, we implemented an algorithm that looks for conditions in a stable operation mode. The pseudocode for initialization is shown in algorithm 1.

While this algorithm allows to find conditions applicable to situations with identical conditions to the horizon of interest, in practical terms for power system operations, a more suitable approach would be the implementation of a receding horizon scheme. We are in the process of studying this problem, and it will be the subject of a future paper.

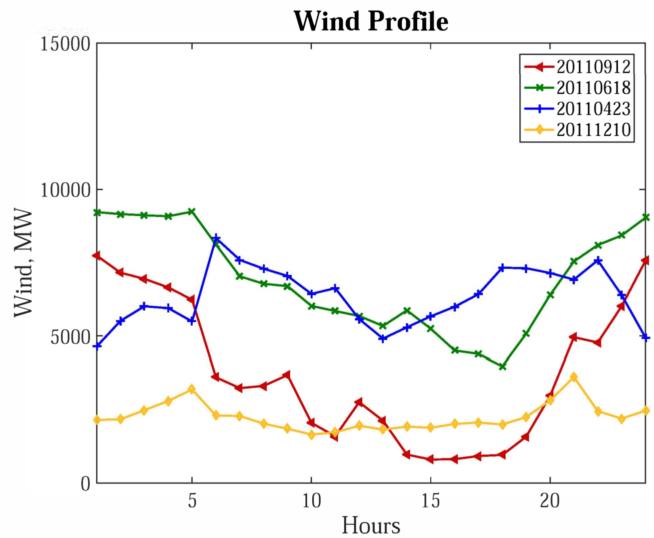

Fig. 2. Centroids for wind Scenarios Considered

Algorithm 1 Initial Conditions for Horizon Problem

Require: Case Information C, Set of ESS prices for charge $\mathscr{L}^c$, Set of ESS prices for discharge $\mathscr{L}^d$, Dispatches of ESS units $\mathscr{P}$, Stored Energy in ESS units $\mathscr{E}$

{1. Initialization Phase}
Run Simple OPF with C
Obtain $(L^{m1}_1, \ldots L^{m1}_n)$ = Initial Prices of $\mathscr{L}^m, m = \{c, d\}$
Obtain $(P^1_1, \ldots P^1_n)$ = Initial Dispatches of $\mathscr{P}$
Obtain $(E^1_1, \ldots E^1_n)$ = Initial Energy Stored of $\mathscr{E}$
{2. Iteration Phase}
repeat
    Run Multiperiod SC-OPF
    d^m_{ij} = difference between prices in iteration i and iteration $j = i - 1$
    d^e_{ij} = difference between energy stored in ESS units in iteration i and iteration $j = i - 1$
    d^p_{ij} = difference between dispatches of ESS units in iteration i and iteration $j = i - 1$
    Assign to $(P^j_1, \ldots P^j_i) = (P^i_1, \ldots P^i_n) = \forall$ ESS dispatches $\in \mathscr{P}$
    Assign to $(E^j_1, \ldots E^j_i) = (E^i_1, \ldots E^i_n) = \forall$ ESS stored energy $\in \mathscr{E}$
    Recompute the distances obtained
until distances below tolerance levels set
Run full problem with established starting conditions

B. Network and Generator Data

We use a 279-node reduction of the network of ERCOT [16] [17], serving 85% of the electric load for the US state of Texas [18]. A one line diagram of this network is shown in Fig. 3

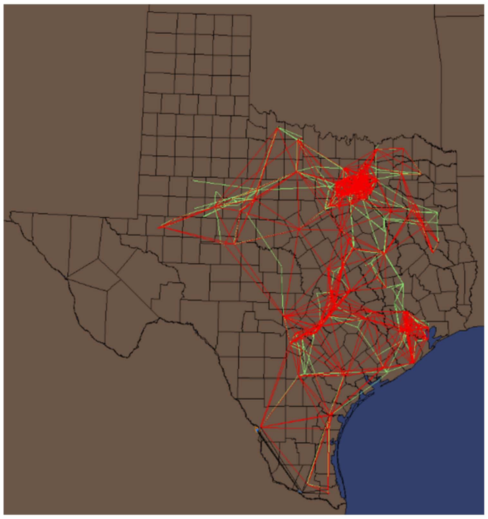

Fig. 3. One Line Diagram for Texas Network, 279 buses

The generator data was part of a large matching exercise of publicly available data sources, including the US Energy Information Administration [19], the US Environmental Protection Agency (USEPA) [20] and Energy Visuals, Inc. ([21], [22]). Further detail about this matching is described in [23], and the information is publicly available at E4ST.org.

Table II shows the generators' information by fuel type. The characteristics summarized include

- Total generation capacity; the median marginal direct cost per MWh
- Median marginal cost per MWh including both direct cost and CO_2 damage
- Mean direct ramp cost per MW of ramp, with Δt indicating the period over which the ramp duration is measured, in this case hours
- Mean ramp cost per MW of ramp including both the direct cost and the CO_2 damage cost of the ramp

TABLE II
SUMMARY OF GENERATION AVERAGE CHARACTERISTICS BY UEL TYPE

	Gen. Cap.[a] (MW)	En. Cost[b] ($/MWh)	En. Cost incl.[c] CO_2 ($/MWh)	Ramp Cost[d] ($/(MW/$\Delta$t))	Ramp Cost incl.[e] CO_2 ($/(MW/$\Delta$t))
Coal	19,552	17.44	56.13	13.84	24.25
Natural Gas	52,538	44.14	67.45	13.52	18.55
Nuclear	5,063	0.00	0.00	30.69	30.69
Hydro	536	10.40	10.40	0.00	0.00
Wind	9,786	0.00	0.00	0.00	0.00
Others	929	37.77	67.39	10.76	15.59

[a] Values shown are peak values
[b] Energy cost excluding CO_2 damage cost (median)
[c] Energy cost including CO_2 damage cost (median)
[d] Average ramp cost excluding CO_2 damage cost (mean)
[e] Average ramp cost including CO_2 damage cost (mean)

IV. RESULTS

We use the reduced network to evaluate the effectiveness of different policies on measures of the overall performance, including the cost of operation (fuel and ancillary services), the amount of load shed observed, the dispatched wind energy and the capacity adequacy requirements to comply with reliability standards [2]. We also internalize environmental externalities, by augmenting the objective function costs [24]. We apply this method to estimate the impacts of five system changes: the addition of wind farms, the addition of a energy storage system such as a battery bank, and three operational policies. The operational policies are the inclusion of ramping direct costs in the objective function, a fee (or cap and trade program) on CO_2 emissions from power generation, and the extension of that fee (or cap and trade program) to the CO_2 emissions resulting from ramping.

The cases simulated can be summarized as follows.

1) **Case 1**: No Wind, Initial System,
2) **Case 2**: Case 1 + 11GW of wind at 92 locations
3) **Case 3**: Case 2 + ESS collocated at largest wind farm, with an energy capacity of 100 MWh and Power capacity of 50MW
4) **Case 4**: Case 2 + "energy CO_2", the part of its CO_2 emission that is proportional to its generation
5) **Case 5**: Case 4 + "Ramping direct cost", including both the fuel cost of ramping and the wear-and-tear cost ramping
6) **Case 6**: Case 5 + "CO_2 cost", where a generator's ramp is equal to the effect of the ramp on the generator's emissions, times an assumed $40 damage cost per ton of CO_2. [25] argues that the risk of catastrophic future damages from climate change merits assuming a substantially higher CO_2 damage cost, but we maintain a conservative estimate
7) **Case 7**: Case 6 + ESS, with the same characteristics as Case 3.

We simulate the operation of the system over 24 consecutive one-hour periods. Table III summarizes key financial results from the cases included for the 24-hour horizon, assuming that the wholesale market for energy is deregulated.

The **E[Total Operating Cost]** are reduced by the use of ESS, as well as the capacity needed for reliability purposes. There is a significant increase in the amount of wind dispatched, which can be argued is one of the objectives of the SO. We will focus our attention on two aspects of the results. First, the Net Revenue for SO increases, driven by congestion in the system. However, the revenue received by wind generators is increased. This is especially important from the policy standpoint because the subsidies that wind generators receive can be decreased once these revenues become self-sustaining. Second, the amount of ramp required over remains constant and decreases slightly once environmental policies are put into place, which means less units need to be committed and in standby for uncertainty mitigation. The conclusions we can draw from the model are likely to maintain the order in less reduced systems, but the order of magnitude may be distorted, due to the network reduction we use and its effects on the results. It can be argued that this is an unavoidable consequence of the losses in information using a Ward equivalent reduction. All of the policies produce a

TABLE III
DAILY SUMMARY OF SYSTEM RESULTS

	Case1	Case2	Case3	Case4	Case5	Case6	Case7
Expected Outcome							
E[Wind Generation] (MW/day)	0.00	26,606.12	26,607.82	26,651.83	26,641.30	26,643.72	26,645.39
E[Conventional Generation](MW/day)	1,575,952.54	1,549,346.35	1,549,341.14	1,549,300.64	1,549,311.16	1,549,308.74	1,549,303.71
LF Up Reserve (MW/day)[a]	14,204.35	39,577.31	39,313.60	41,766.17	40,508.22	40,438.19	40,410.45
LF Down Reserve (MW/day)[a]	13,176.31	39,235.84	38,721.78	40,562.79	39,814.86	39,538.44	39,637.61
Contingency Reserve (MW/day)	28,884.00	66,717.84	65,841.28	68,192.00	67,697.20	67,664.17	66,897.26
E[Load Shed]	0.00	0.08	0.08	0.08	0.08	0.08	0.08
E[Generation Cost]	62,870.33	60,291.30	60,280.71	105,718.02	105,736.02	105,742.58	105,719.47
E[Ramp Wear Cost]	0.00	0.00	0.00	0.00	698.83	963.66	696.68
LF Ramp-Up Reserve Cost	14.23	37.77	37.51	42.57	41.95	42.07	41.65
LF Ramp-Down Reserve Cost	12.86	36.95	36.45	40.29	40.43	39.77	40.11
Contingency Reserve Cost	27.62	62.23	61.26	63.59	63.13	63.13	62.33
E[Total Operating Cost]	62,925.04	60,428.30	60,407.93	105,864.52	106,580.40	106,851.25	106,547.23
E[Net Revenue for Conventional Generation]	154,979.89	148,359.88	148,324.40	214,989.09	214,613.27	214,083.86	214,606.23
E[Net Revenue for Wind Generation]	0.00	2,667.24	2,668.35	4,131.31	4,095.32	4,075.46	4,094.84
E[Net Revenue for SO]	13,029.01	14,017.07	14,015.39	21,170.63	21,433.60	21,521.06	21,450.57
E[Total Wholesale Cost]	230,933.93	225,472.49	225,416.07	346,155.55	346,722.60	346,531.64	346,698.87
E[Load Not Served] * VOLL[b]	0.00	0.79	0.82	0.79	0.79	0.79	0.79
E[Total Cost for Customers]	230,933.93	225,473.27	225,416.89	346,156.34	346,723.39	346,532.43	346,699.66

[a] Load-Following Ramp Reserve.
[b] Value of Lost Load.

TABLE IV
PEAK HOUR SUMMARY OF SYSTEM RESULTS

	Case1	Case2	Case3	Case4	Case5	Case6	Case7
Expected Outcomes (MWh)							
'Peak Hour'	15.00	15.00	15.00	15.00	15.00	15.00	15.00
E[Load Served]	73,510.95	73,510.95	73,510.95	73,510.95	73,510.95	73,510.95	73,510.95
E[Load Not Served]	0.00	0.00	0.00	0.00	0.00	0.00	0.00
E[Conventional Generation]	72,747.05	71,909.96	71,870.95	71,909.96	71,909.96	71,909.96	71,859.96
E[Wind Generation]	0.00	837.09	837.09	837.09	837.09	837.09	837.09
E[Exogenous Imports]	763.90	763.90	763.90	763.90	763.90	763.90	763.90
E[Electric Energy Delivered]	73,510.95	73,510.95	73,510.95	73,510.95	73,510.95	73,510.95	73,510.95
Maximum Outcomes (MW)							
All Load Served	73,510.95	73,510.95	73,510.95	73,510.95	73,510.95	73,510.95	73,510.95
Conventional Generation, Intact	72,747.05	72,156.12	72,106.14	72,156.12	72,156.12	72,156.12	72,106.12
Conventional Generation	73,950.55	73,359.62	73,309.62	73,359.62	73,359.62	73,359.62	73,309.62
Wind Generation	0.00	1,873.20	1,873.20	1,873.20	1,873.20	1,873.20	1,873.20
LF Ramp-Up	0.00	974.50	885.39	974.50	974.50	974.50	974.52
LF Ramp-Down	115.47	1,310.21	1,310.23	1,310.21	1,310.21	1,310.21	1,269.15
Contingency Ramp	1,203.50	2,217.31	2,158.27	2,217.31	2,217.31	2,217.31	2,217.31
Conventional Generating Units	130,152.96	129,112.92	129,024.92	129,112.92	129,112.92	129,112.92	129,024.92

positive net operating benefit over the simulated day.

Table IV summarizes the results for the peak hour of the day. In terms of dispatches, the operational changes do not alter the patterns at the peak in most measures considered. The main differences lie in the displacement of conventional generation by ESS resources, reducing the peak generation by 50MW in the intact system. While wind dispatches change over the whole day, the peak s remarkably stable in terms of this resource. The overall policies' impacts on the individual categories of total net benefit vary widely as illustrated in Tables III.

Fig. 4 shows the operation of the storage system, with the maximum (upper dashed line), minimum (lower dashed line), and expected (solid line) charge status of the energy storage system. The ESS charges or discharges in response to lower- or higher-than-expected generation needs, reducing the need for conventional generation reserves as shown in Table IV.

V. CONCLUSIONS

This paper presents a model aimed at evaluating the effects of integrating Renewable Energy Sources (RES) in the electricity system, from the perspective of a system operator, taking into account the cost of Carbon Dioxide ($C0_2$) emissions. Aside from the optimization formulation, our method of

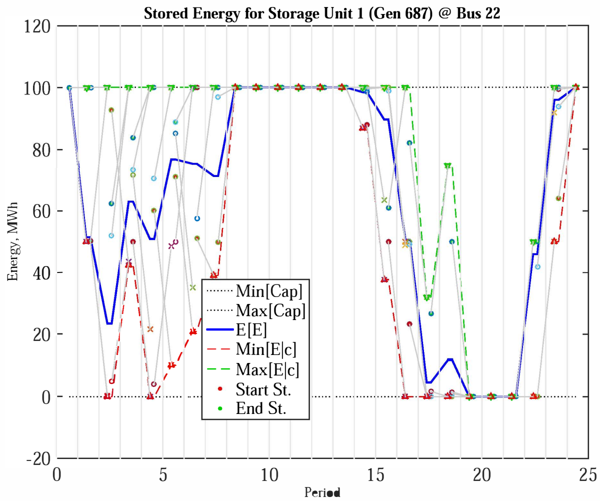

Fig. 4. Energy in Single Storage Unit

estimating the net benefits of system changes has four other innovations. First, it statistically estimates the cost and CO_2 emission consequences of each generator's electricity output and ramping decisions from publicly available data. Second and third, our method includes creating a novel, modified Ward reduction of the grid and a thorough generator dataset, also from publicly available information sources. Fourth, it combines technical and economic considerations to produce a comprehensive measure of net operating benefit in the context of a power grid, and disaggregates that into the effects on consumers, producers, system operators, government, and CO_2 damage.

We illustrate the use of the method using a single day of operations with a high demand (summer). The method can be used to estimate net operating benefits over a year, by simulating a representative sample of all of the days of the year. The use of storage supports the overall operation of the system and reduces the peak capacity needed. Future studies can include the cost of capital and the planning implications of this method.

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