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A Comparison of Day-Ahead Wholesale Market: Social Welfare vs Industrial Demand Side Management

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***Abstract*—The intermittent nature of renewable energy has been discussed in the context of the operational challenges that it brings to electrical grid reliability. In contrast, Demand Side Management (DSM) with its ability to allow customers to adjust electricity consumption in response to market signals has often been recognized as an efficient way to mitigate the variable effects of renewable energy. DSM has also been advocated for its ability to increase system efficiency and reduce system costs. However, the industrial & academic literature have taken divergent approaches to DSM implementation. Academic studies often implement demand side management on the basis of a social welfare maximization. Meanwhile, industrial implementations minimize costs where customers are now compensated for load reductions from a predefined baseline of electricity consumption that would have occurred without DSM. This paper aims to rigorously compare these two different approaches in a day-ahead wholesale market context using the same system configuration and mathematical formalism. The comparison showed that while the social welfare model uses a stochastic net load composed of two terms, the industrial DSM model uses a stochastic net load composed of three terms. It is thus more prone to error and more likely requires more control activity in subsequent layers of enterprise control. The two DSM models also mitigate the stochastic net load in fundamentally different ways and incentivize greater participation under very different conditions of renewable energy integration and conventional demand.**

NOMENCLATURE

GC	subscript for dispatchable (controllable) generators (e.g. thermal plants)
GS	subscript for stochastic generators (e.g. wind, solar photo-voltaic)
DC	subscript for dispatchable (controllable) demand units (i.e. participating in DSM)
DS	subscript for stochastic demand units (i.e. conventional load)
i	index of dispatchable generators
j	index of dispatchable demand unit
k	index of stochastic generators
l	index of stochastic demand unit
t	index of unit commitment time intervals
N_{GC}	Number of dispatchable generators
N_{DC}	Number of dispatchable demand units
N_{GS}	Number of stochastic generators
N_{DS}	Number of stochastic demand units
T	Number of unit commitment time intervals
P_{GCit}	dispatched power generation at the i^{th} dispachable generator in the t^{th} time interval
P_{DCjt}	dispatched power consumption at the j^{th} dispatchable demand unit in the t^{th} time interval
$\hat{P}_{DCjt}$	forecasted power consumption of the j^{th} dispatchable demand unit in the t^{th} time interval
$\tilde{P}_{DCjt}$	baseline power consumption of the j^{th} dispatchable demand unit in the t^{th} time interval
$\hat{P}_{GSkt}$	forecasted power generation at the k^{th} stochastic generator in the t^{th} time interval
$\hat{P}_{DSlt}$	forecasted power consumption of the l^{th} stochastic demand unit in the t^{th} time interval
$\underline{P_{GCi}}$	min. capacity of the i^{th} dispatchable generator
$\underline{P_{DCj}}$	min. capacity of the j^{th} dispatchable demand unit
$\underline{R_{GCi}}$	min. ramping capability of the i^{th} dispatchable generator
$\underline{R_{DCj}}$	min. ramping capability of the j^{th} dispatchable demand unit
$\overline{P_{GCi}}$	max. capacity of the i^{th} dispatchable generator
$\overline{P_{DCj}}$	max. capacity of the j^{th} dispatchable demand unit
$\overline{R_{GCi}}$	max. ramping capability of the i^{th} dispatchable generator
$\overline{R_{DCj}}$	max. ramping capability of the j^{th} dispatchable demand unit
$\mathcal{C}_{GCi}$	cost of the i^{th} dispatchable generator
$\mathcal{S}_{GCi}$	startup cost of the i^{th} dispatchable generator
$\mathcal{D}_{GCi}$	shutdown cost of the i^{th} dispatchable generator

$\mathcal{R}_{GCit}$ running cost of the i^{th} dispatchable generator in the t^{th} time interval

A_{GCi} quadratic cost function coefficient of the i^{th} dispatchable generator

B_{GCi} linear cost function coefficient of the i^{th} dispatchable generator

ζ_{GCj} cost function constant of the i^{th} dispatchable generator

$\mathcal{U}_{DCj}$ demand utility of the j^{th} dispatchable demand unit

$\mathcal{S}_{DCj}$ startup utility of the j^{th} dispatchable demand unit

$\mathcal{D}_{DCj}$ shutdown utility of the j^{th} dispatchable demand unit

$\mathcal{R}_{DCjt}$ running utility of the j^{th} dispatchable demand unit in the t^{th} time interval

A_{DCj} quadratic utility function coefficient of the j^{th} dispatchable demand unit

B_{DCj} linear utility function coefficient of the j^{th} dispatchable demand unit

ζ_{DCj} utility function constant of the j^{th} dispatchable demand unit

$\mathcal{C}_{DCj}$ cost of the j^{th} virtual generator

$\mathbb{S}_{DCj}$ startup cost of the j^{th} virtual generator

$\mathbb{D}_{DCj}$ shutdown cost of the j^{th} virtual generator

$\mathbb{R}_{DCjt}$ running cost of the j^{th} virtual generator in the t^{th} time interval

$\mathbb{A}_{DCj}$ quadratic cost function coefficient of the j^{th} virtual generation

$\mathbb{B}_{DCj}$ linear cost function coefficient of the j^{th} virtual generation

ξ_j cost function constant of the j^{th} virtual generation

w_{GCit} binary variable for the state of the i^{th} dispatchable generator in the t^{th} time interval

u_{GCit} binary variable for the startup state of the i^{th} dispatchable generator in the t^{th} time interval

v_{GCit} binary variable for the shutdown state of the i^{th} generator in the t^{th} time interval

w_{DCjt} binary variable for the state of the i^{th} dispatchable demand unit in the t^{th} time interval

u_{DCjt} binary variable for the startup state of the j^{th} dispatchable demand unit in the t^{th} time interval

v_{DCjt} binary variable for the shutdown state of the j^{th} dispatchable demand unit in the t^{th} time interval

ω_{DCjt} binary variable for the state of the j^{th} virtual generation in the t^{th} time interval

μ_{DCjt} binary variable for the startup state of the j^{th} virtual generation at the beginning of the t^{th} time interval

ν_{DCjt} binary variable for the shutdown state of the j^{th} virtual generation at the beginning of the t^{th} time interval

I. INTRODUCTION

The intermittent nature of renewable energy has been discussed in the context of the operational challenges that it brings to electrical grid reliability [1]–[3]. The fast fluctuations in renewable energy generation require high ramping capability which must be balanced by dispatch able energy resources. Additionally, a sudden loss of renewable generation can threaten grid reliability in the absence of adequate generation reserves.

In contrast, Demand Side management (DSM) with its ability to allow customers to adjust electricity consumption in response to market signals has often been recognized as an efficient way tot mitigate the variable effects of renewable energy [4]–[6]. DSM has also been advocated for its ability to increase system efficiency and reduce system costs by peak load shaping and shifting [7], [8]. By allowing and encouraging customers to adjust their electricity consumption in response to market signals, DSM provides additional dispatchable resources [9], [10] which can potential offset imbalances caused by renewable energy and reduce the need for more expensive generators with high ramping capability. It also increases the bulk electric system reliability by disengaging some loads at challenging periods. Meanwhile, DSM increases the utilization of generating capacities that would have been otherwise idle during off-peak hours, thus reducing the real cost of renewable integration. [11] The electricity supply side, load-reducing customers and non-load-reducing customers all benefit economically from load reductions [12]–[14]. The deregulation of electricity markets has also motivated more active DSM programs [15]–[19]. As a result, Independent System Operators (ISOs) and Reliability Transmission Organizations (RTOs) have been implementing DSM for its potential to lower market prices, reduce price volatility, improve customer options, and increase the elasticity from wholesale to retail market [20].

Despite its recognized importance [21]–[23], the industrial and academic literature seem to have taken divergent approaches to DSM implementation. Research on DSM has addressed the maximization of customer utility, the minimization of customer discomfort, and the stabilization of electricity prices [24]–[27]. A common approach among academic researchers is to maximize social welfare defined as the net benefits from electricity consumption and generation based on the utility of dispatchable demand [24], [26]–[29]. In the meantime, the industrial trend has been to introduce "virtual generators" in which customers are compensated for load reductions from baseline electricity consumption [16], [17], [30]–[33]. Such a baseline is defined as the electricity consumption that would have occurred without DSM and is estimated from historical data from the prior year [34]–[36]. Such baselines are subject to manipulations and false load reductions can be created for more compensations [37], [38]. While the differences between the two methods have often been a part of policy discussions, they have not been rigorously studied. This papers aims to rigorously compare these two different approaches in a day-ahead wholesale market context using the same system configuration and mathematical formalism.

The remainder of this paper develops in five sections. Section II summaries highlights from both the academic literature and industrial documents. Section III presents the mathematical models for both the social welfare and industrial methods of unit commitment with dispatchable demands as well as the model reconciliation. Section IV presents the test case and methodology. The results and conclusions from the case study for both models are presented and discussed in Section V. The paper concludes in Section VI.

II. Background

This section summarizes the two contrasting approaches to demand dispatching: social welfare methods often found in academia and load reduction from baseline methods implemented in industry.

A. Academic Literature

A popular approach in the academic literature is to adopt a maximal social welfare problem formulation. Elastic demand is characterized by its utility U – the benefit from electricity consumption, and generation is characterized by its cost C. [39]. The maximize social welfare determines the dispatch schedule and price for suppliers and customers together [24]. In an economic dispatch context, social welfare has been defined in textbooks as [39]:

$$SW(P_G, P_D) = \sum_{j=1}^{m} U_j(P_{Dj}) - \sum_{i=1}^{n} C_i(P_{Gi}) \tag{1}$$

where P_D and P_G represent the individual demands and generators respectively; m and n represent the number of demands and generators. Assuming lossless transmission, the system power balance constraint becomes [39]:

$$\sum_{i=1}^{n} P_{Gi} = \sum_{j=1}^{m} P_{Dj} \tag{2}$$

The objective function in (1) and the constraint in (2) constitute the simplest form of social welfare maximization. As mentioned and cited in the introduction, It has has not been implemented by the electricity industry.

B. Industrial Practice

The industrial approach to dispatching demand minimize the total cost of dispatch able generation and virtual generation. A curtailment service provider (CSP) represents the demand units participating in the wholesale energy market. Each CSP has an "administratively-set" electricity consumption baseline as an estimate of consumption without DSM incentives and from which load reductions are measured. The CSP can participate in one of several wholesale energy markets; one of them being the Day-Ahead Scheduling Reserve Market (DASR) where where generation suppliers, load serving entities, and CSPs bid through ISO/RTO [40]. The bidding process determines the dispatched resources as well as the electricity price for the next day [33]. Accepted load reductions are obliged to commit and are subsidized by ISO/RTO based on the bidding price compared to the Locational Marginal Pricing (LMP) and the Retail Rates (GT) [13].

III. Mathematical Models

This section now describes the mathematical formulation for both the social welfare and industrial load reduction models.

A. Social Welfare Maximization

The formulation of maximal social welfare problem is as follows. Unlike the economic dispatch problem presented in Section II-A, the unit commitment model schedules the dispatchable resources and determines their states over multiple time intervals. The optimization goal remains to maximize the social welfare (Equation 3, or to minimize the loss in social welfare (over all time intervals).

$$SW = \sum_{t=1}^{T} \left[\sum_{j=1}^{N_{DC}} \mathcal{U}_{DCj}(P_{DCjt}) - \sum_{i=1}^{N_{GC}} \mathcal{C}_{GCi}(P_{GCit}) \right] \tag{3}$$

The optimization program in Section II-A also also assumed that all generators and loads are dispatchable. For greater practicality, this assumption is relaxed so that stochastic generation (i.e. renewable energy) and stochastic demand (i.e. conventional load) can be included. These are taken as fixed exogenous quantities whose costs and utilities are independent from dispatch decisions and which must be balanced by dispatchable generation and demand units. The social welfare objective function $\mathcal{W}$ is given by

$$\mathcal{W} = \sum_{t=1}^{T} \left[\sum_{i=1}^{N_{GC}} \mathcal{C}_{GCi}(P_{GCit}) - \sum_{j=1}^{N_{DC}} \mathcal{U}_{DCj}(P_{DCjt}) \right] \tag{4}$$

where both the generation cost $\mathcal{C}_{GCi}$and demand utility $\mathcal{U}_{DCj}$ have a startup, a shutdown, and a running component shown in Equation (5) and Equation (6).
$\forall i = 1, ..., N_{GC}, j = 1, ..., N_{DC}, \forall t = 1, ..., T:$

$$\mathcal{C}_{GCi}(P_{GCit}) = u_{GCit}(\mathcal{S}_{GCi}) + v_{GCit}(\mathcal{D}_{GCi}) + w_{GCit}\left[\mathcal{R}_{GCi}(P_{GCit})\right] \tag{5}$$

$$\mathcal{U}_{DCj}(P_{DCjt}) = u_{DCjt}(\mathcal{S}_{DCj}) + v_{DCjt}(\mathcal{D}_{DCj}) + w_{DCjt}\left[\mathcal{R}_{DCj}(P_{DCjt})\right] \tag{6}$$

where the running cost for generators $\mathcal{R}_{GCit}$ and running utility for demands $\mathcal{R}_{DCjt}$ are modeled as quadratic functions to capture the change in marginal costs and marginal utilities.

$$\begin{aligned} \mathcal{R}_{GCi}(P_{GCit}) &= A_{GCi}(P_{GCit})^2 + B_{GCi}(P_{GCit}) + \zeta_{GCi} \\ \mathcal{R}_{DCj}(P_{DCjt}) &= A_{DCj}(P_{DCjt})^2 + B_{DCj}(P_{DCjt}) + \zeta_{DCj} \end{aligned} \tag{7}$$

The objective function is optimized subject to the system power balance constraint in Equation (8), the capacity constraint for both the dispatchable generators in Equation (9) and dispatchable demands in Equation (10),the ramping constraint for dispatchable generation in Equation (11) and dispatchable demand in Equation (12), and the logical constraints Equations (13) and (14) respectively.

$$\begin{aligned}&\forall t=1,...,T\\&\sum_{i=1}^{N_{GC}} P_{GCit}-\sum_{j=1}^{N_{DC}} P_{DCjt}=\sum_{k=1}^{N_{DS}} \hat{P}_{DSkt}-\sum_{l=1}^{N_{GS}} \hat{P}_{GSlt}\end{aligned} \tag{8}$$

$$w_{GCit} * \underline{P_{GCi}} \leq P_{GCit} \leq w_{GCit} * \overline{P_{GCi}} \tag{9}$$

$$w_{DCjt} * \underline{P_{DCj}} \leq P_{DCjt} \leq w_{DCjt} * \overline{P_{DCj}} \tag{10}$$

$$\begin{aligned}&R_{GCit}=P_{GCit}-P_{GCi(t-1)}\\&\underline{R_{GCi}} \leq R_{GCit} \leq \overline{R_{GCi}}\end{aligned} \tag{11}$$

$$\begin{aligned}&R_{DCjt}=P_{DCjt}-P_{DCj(t-1)}\\&\underline{R_{DCj}} \leq R_{DCjt} \leq \overline{R_{DCj}}\end{aligned} \tag{12}$$

$$w_{GCit}=w_{GCi(t-1)}+u_{GCit}-v_{GCit} \tag{13}$$

$$w_{DCjt}=w_{DCj(t-1)}+u_{DCjt}-v_{DCjt} \tag{14}$$

B. Industrial Practice: Cost Minimization with Demand Baseline

The formulation of the industrial Unit Commitment model is as follows. Much like the social welfare model, the industrial unit commitment model determines the setpoints for all dispatch able resources. In contrast, however, the optimization goal industrial approach is to minimize the total cost of dispatchable generators and virtual generators over all time intervals of the SCUC period, where the cost of virtual generation is the compensation paid to the customers for reducing their consumption from predefined demand baseline. The industrial demand side mangement objective is given in Equation 15.

$$\sum_{t=1}^{T}\left[\sum_{i=1}^{N_{GC}} \mathcal{C}_{GCi}(P_{GCit})+\sum_{j=1}^{N_{DC}} \mathcal{C}_{DCj}(\tilde{P}_{DCjt}-P_{DCjt})\right] \tag{15}$$

where the costs of the dispatchable generation remain the same as in Equation (5) and the costs of dispatchable demand shown in Equation (16) also have startup, shutdown, and running cost.

$$\begin{aligned}&\forall i=1,...,N_{GC},\forall t=1,...,T\\&\mathcal{C}_{DCj}(\tilde{P}_{DCjt}-P_{DCjt})=\\&\mu_{DCjt}(\mathbb{S}_{DCj})+\nu_{DCjt}(\mathbb{D}_{DCj})+\omega_{DCjt}\left[\mathbb{R}_{DCj}\right]\end{aligned} \tag{16}$$

The running cost is similarly modeled as a quadratic function of the load reduction from the baseline.

$$\begin{aligned}&\mathbb{R}_{DCj}(\tilde{P}_{DCjt}-P_{DCjt})=\\&\mathbb{A}_{DCj}(\tilde{P}_{DCjt}-P_{DCjt})^2+\mathbb{B}_{DCj}(\tilde{P}_{DCjt}-P_{DCjt})+\xi_{DCj}\end{aligned} \tag{17}$$

The objective function is optimized subject to same system power balance constraint in (8). Both the dispatchable generation and virtual generation are subject to the capacity limits in Equations (9) and (18) respectively, the ramping limits in Equations (11) and (12) respectively, and the logical constraints in Equations (13) and (19) respectively.

$$\begin{aligned}&\forall j=1,...,N_{DC},\forall t=1,...,T\\&\omega_{DCjt} * \underline{\tilde{P}_{DCjt}-P_{DCjt}} \leq \tilde{P}_{DCjt}-P_{DCjt}\\&\tilde{P}_{DCjt}-P_{DCjt} \leq \omega_{DCjt} * \overline{\tilde{P}_{DCjt}-P_{DCjt}}\end{aligned} \tag{18}$$

$$\overline{w}_{DCjt}=\overline{u}_{DCj(t-1)}+\overline{u}_{DCjt}-\overline{v}_{DCjt} \tag{19}$$

C. Model Reconciliation

For the fairness of comparison, the utility function from social welfare model and the virtual generation cost in the industrial model need to be reconciled. The cost of virtual generation in the industrial model is set up to be consistent with loss in utility in SW model with the same change in dispatchable demand. The economics rationale for this is that the customers are only willing to cut down electricity consumption if their marginal loss in utility is subsidized by the marginal cost in virtual generation.

$$\begin{aligned}&-\mathcal{U}_{DCj}(P_{DCj})+\mathcal{U}_{DCi}(P_{DCj}+\delta P_{DCj})=\\&\mathcal{C}_{DCj}(\tilde{P}_{DCj}-P_{DCj})-\mathcal{C}_{DCj}(\tilde{P}_{DCj}-P_{DCj}-\delta P_{DCj})\end{aligned} \tag{20}$$

Rearranging quadratic and linear terms in Equation (20) yields Equation (21). It shows an important result that the cost function of load reduction is dependent on the choice of baseline.

$$\begin{aligned}&\mathbb{A}_j=-A_j\\&\mathbb{B}_j=2 * A_j * \tilde{P}_{DCj}+B_j\end{aligned} \tag{21}$$

Now that the these two optimization programs are well defined and reconciled with each other, they can be compared in a specific case study.

IV. Case Study Methodology

The case study consists of a day-ahead unit commitment in a wholesale market. It is simulated for both the social welfare and industrial DSM methods. The same system configuration and data are used to compare the two optimization programs presented in the previous section. The results are studied for their differences in the dispatched energy resources, resulting social welfare, and system costs. Data is drawn from the *Reliability Test System(RTS)-1996* [43], [44] and the Bonneville Power Administration (BPA) website [41], [42]. This is detailed in the following subsections.

A. Time Scale

For a day-ahead UC program, the time span is 24 hours. A 1-hour time interval is chosen for the case study.

B. Stochastic Generation, Stochastic Demand, & Demand Baseline

The stochastic generation is taken as the renewable energy generation. Because it only appears in the power system balance constraint, only aggregate renewable energy generation is required. It is drawn from the wind forecast data published on the Bonneville Power Administration (BPA) website for

TABLE I
STOCHASTIC DEMAND AND GENERATION LEVELS IN MW [41], [42]

Hour of the Day	1	2	3	4	5	6	7	8	9	10	11	12
Load Forecast 05/15/2013 (MW)	5217	5022	4872	4807	4819	4898	4996	5305	5741	5976	6016	6030
Wind Forecast 05/15/2013 (MW)	1977	1580	1574	1788	1898	1799	2019	2235	2075	2026	2169	2084
Hour of the Day	13	14	15	16	17	18	19	20	21	22	23	24
Load Forecast 05/15/2013 (MW)	6049	6011	5996	6013	6036	6063	6080	6096	6204	6095	5708	5311
Wind Forecast 05/15/2013 (MW)	2089	2264	2505	2826	2948	3143	2725	2658	2133	1513	1335	1350

TABLE II
DISPATCHABLE GENERATOR PARAMETERS [43], [44]

N_{GC}	72									
Unit Type	Generator Index	$\overline{P}_{GCi}$ (MW)	$\underline{P}_{GCi}$ (MW)	$\overline{R}_{GCi}$ (MW/MI)	$\underline{R}_{GCi}$ (MW/MI)	ζ_{GCi} ($)	B_{GCi} ($/MW)	A_{GCi} ($\$/MW^2$)	S_{GCi} ($)	D_{GCi} ($)
U12	16,17,18,19,20,49,50,51,52,53,82,83,84,85,86	12	2.4	1	-1	37.8	26.8	10	874	0
U20	01,02,05,06,34,35,38,39,67,68,71,72	20	4.0	3	-3	163.3	39.2	10	115	0
U76	03,04,07,08,36,37,40,41,69,70,73,74	76	15.2	2	-2	151.2	13.5	3	1401	0
U100	09,11,42,44,75,77	100	20.0	7	-7	312.8	21.7	0.6	5750	0
U155	21,22,31,32,54,55,64,65,87,88,97,98	155	31.0	3	-3	210.4	11.0	3	611	0
U197	45,46,47,78,79,80	197	39.4	3	-3	315.1	21.9	0.6	10189	0
U350	33,66,99	350	70.0	4	-4	181.0	11.0	0.48	4500	0
U400	23,24,56,57,89,90	400	80.0	20	-20	343.7	5.6	0.48	4700	0

TABLE III
DISPATCHABLE DEMAND UNIT PARAMETERS

$\underline{P}_{DCj}$ (MW)	$\overline{R}_{DCj}$ (MW/h)	$\underline{R}_{DCj}$ (MW/h)	ζ($)	B_j ($/MW)	A_j ($\$/MW^2$)	S_{DCj} ($)	D_{DCj} ($)
0	$\overline{P}_{DCj}/2$	-$\overline{P}_{DCj}/2$	0	195	-0.2	0	0

May 12, 2013 [42]. The raw data for the load forecast has a sampling resolution of 5 minutes. It was down sampled by taking hourly averages. The resulting numbers are provided in Table I.

Similarly, the stochastic demand is taken as the conventional load. It's aggregate value is drawn from the BPA load repository for the same day [41] and downsampled. The resulting numbers provided in Table I and only apply to the demand side units participating in the DSM program.

For the sake of simplicity, a dispatachable demand unit was assumed to exist on each bus. It's baseline was set to a constant value equal to 12% of the peak demand published for that bus in the RTS-1996 test case. Furthermore, this work assumes that this baseline is equal to the maximum capacity of the dispatchable demand unit. $\tilde{P}_{DCj} = \overline{P}_{DCj}$.

C. Dispatchable Generation & Dispatchable Demands

Dispatchable generators refer to the generation plants that can be fully controlled. Their dispatch level is a key quantity of interest in this study. Dispatchable demands come from the DSM participants and are assumed to be fully controllable without error.

Dispatchable generator parameters are listed in Table II [43]. The startup cost is based on hot start. Slack generators, regulating generators and hydro generators do not participate in unit commitment, and therefore are excluded from the tables. The system has a total dispatchable generating capacity of 8424 MW available for day-ahead unit commitment.

Each aggregated dispatchable demand is assumed to occur at each bus. The utility function coefficients for all the dispatchable demand units are assumed to be equal and time-invariant. They are provided in Table III. The minimum and maximum capacity limit of each dispatchable demand unit is assumed to be zero and 12% of the peak load at the corresponding bus. It is assumed that each dispatchable demands needs two hours to fully ramp between zero and maximum consumption. For simplicity, no load recovery is considered because we assume the customers base their electricity consumption only on the current utility and electricity cost. The startup and shutdown costs have entirely different physical meanings in the social welfare and industrial DSM models. For the fairness of comparison, the startup and shutdown costs are neglected (i.e. set to zero) in this case study.

D. Computational Methods

In the simulation, MATLAB is used to import data and set up test case. GAMS is interfaced with MATLAB to run the optimization problem. CPLEX is chosen as an optimization engine since all optimization problems are convex function minimization. It takes approximately 70 seconds and 50 seconds to run each SW and industrial method optimization respectively on an $Intel\ Core^{TM}\ i3$ processor.

V. RESULTS & DISCUSSION

The two demand side management optimization programs are studied for their dispatch levels, resulting social welfare, and system costs.

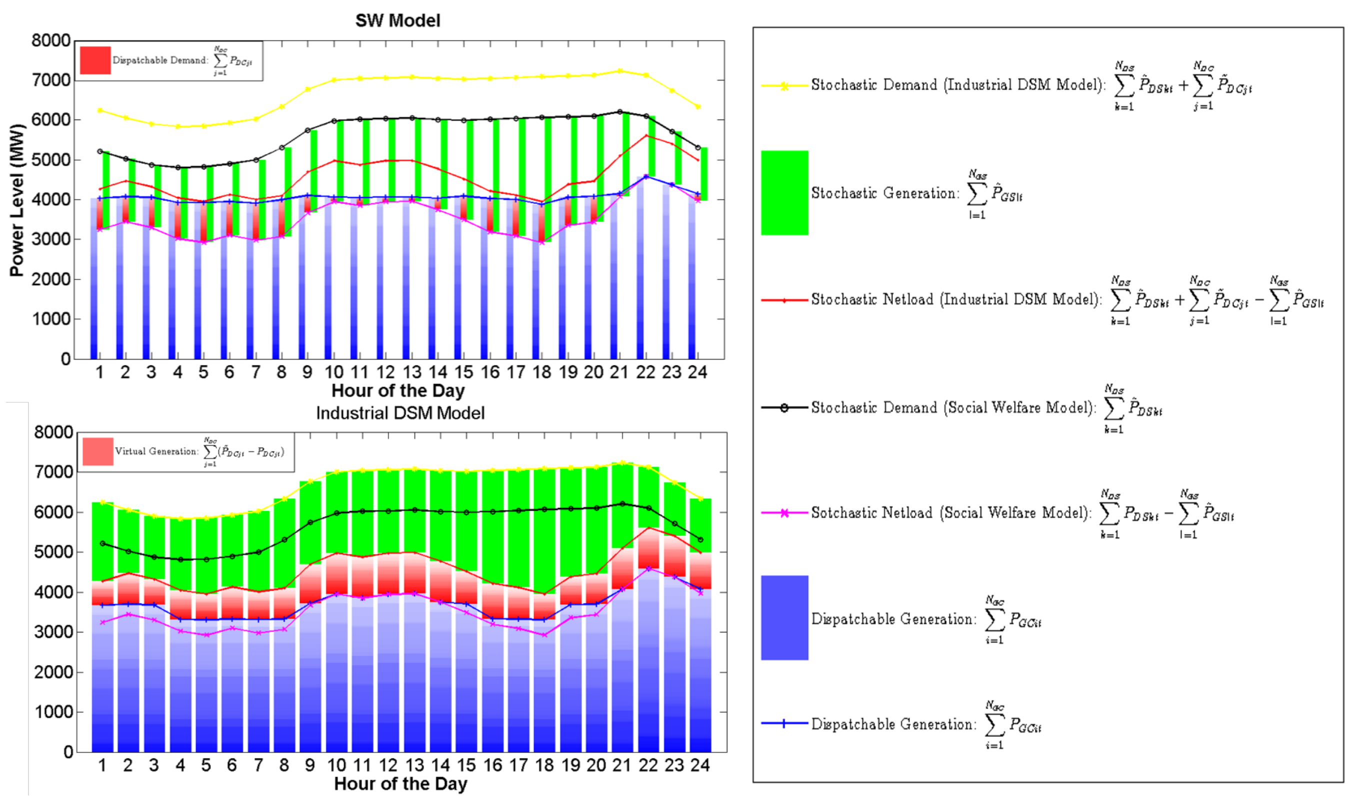

Fig. 1. Social Welfare & Industrial DSM Model Unit Commitment

A. Dispatch Levels

Making a rigorous and fair comparison between the two optimization programs requires borrowing the concepts from each optimization program and artificially applying into the domain of the other. That said, Figure 1a and 1b show the dispatch levels of the two social welfare and industrial demand side management optimization programs. The solid black line represents the stochastic demand level. The solid yellow line adds the dispatchable demand baseline to the black line. This is of little significance in the social welfare model. It only serves to show where the stochastic demand would have been if the dispatchable demand units had not entered the DSM program. Returning to the black stochastic demand line, subtracting the stochastic generation from it gives the magenta line: the stochastic net load line in the social welfare model. The sum of dispatchable generation in blue and the sum of dispatchable demand in red must meet this line to achieve power system balance. Interestingly, the red line in the social welfare model represents the frontier of all the dispatchable demand units consumed at their maximum level (i.e. artificially set to the baseline level in the industrial DSM model.)

The mechanics of the industrial DSM model is entirely different. The solid black line still represents the stochastic demand level. However, the yellow line now serves a real purpose. The subtraction of the stochastic generation in green from the yellow line gives the magenta line: the stochastic net load in the industrial DSM model. The sum of dispatchable generation in blue and the sum of dispatchable demand in red must meet this line to achieve power system balance. Interestingly, the magenta line now represents the frontier of all the virtual generators achieved their maximum load reduction (i.e. virtual generation).

That the stochastic net load line in the social welfare and industrial DSM models are different is an important observation. In the former, it is composed of two terms. In the latter, it is composed of the same two terms plus a third. Therefore, unless the third terms systematically rejects the errors in the first two terms, it is reasonable to conclude that the stochastic netload line in the industrial DSM model is more error prone than its social welfare counterpart.

Returning to the social welfare dispatch shown in Figure 1a, the dispatched generation line appears to remain relatively constant around 4000MW for much of the day. In the meantime, the dispatchable demand varies substantially from nearly zero to approximately 1GW over the course of the day. An interesting phenomenon occurs when the stochastic generation is too low or too high. For example, in Hours 22 & 23, the stochastic generation is low and the dispatchable generation must rise to meet the stochastic netload. This shows that social welfare demand side management does not help mitigate renewable energy down-ramp events. That said, the social welfare model would still incentivize greater demand side participation in this case because it would send a long term that would lower the stochastic demand and stochastic net load curves. On the other hand, in Hours 5 & 18, the stochastic generation is so high that it reaches the maximum capacity of the dispatchable demand. This shows that in the case of an abundance of renewable energy, the social welfare model encourages greater demand side participation. The alternative would be to waste this energy in the form of renewable energy curtailment.

This behavior can be contrasted to the industrial DSM dispatch in Figure 1b. The dispatched generation line appears to vary significantly over the course of the day. In the meantime, the dispatchable demand remains fairly constant over the course of the day. This inversion in the variability of the dispatched generation and storage between the two DSM models is a subject for further investigation. The same hours can be studied for when the stochastic generation is too low or too high. In Hours 22 & 23, again the stochastic generation is too low and the virtual generators appear to be at capacity. The dispatchable generation must rise to meet the netload. As in the case of the social welfare model, the industrial DSM model is incapable of mitigating renewable energy down-ramp events although a long term signal for greater demand side management would be created. Interestingly, Hours 5 & 18 no longer require the full capacity of virtual generation in the industrial DSM case. This means that although there is an abundance of renewable energy, there is no large incentive to expand demand side participation. These incentives instead occur in Hours 10-13 when the stochastic demand and baseline is high but not enough renewable energy exists to bring down the industrial DSM netload.

Figure 2 shows the social welfare results for both simulations. Although, the industrial DSM model does not optimize social welfare, Equation 3 can still be used to evaluate the consequent social welfare for both cases. As expected, the social welfare model provides consistently higher social welfare values. The hourly social welfare value is highest in Hours 17-20 when the stochastic generation is high the stochastic net load is low. In contrast, it is lowest in Hours 21-23 when the stochastic generation is low and the stochastic net load is high. The large difference in social welfare values that arise over hours 10-13 is due to the discrepancy in the dispatch in the relative quantities of generation and demand. Similarly, the system cost can be evaluated for both cases using Equation 15. The resulting costs are different for the two models.

VI. Conclusion

The industrial & academic literature have taken divergent approaches to demand side management implementation. While academic implementations have sought to optimize social welfare, industrial implementations optimize total costs where virtual generators are compensated for their load reduction from a predefined baseline. This work has rigorously compared the two methods using the same test case. The comparison showed that while the social welfare model uses a stochastic net load composed of two terms, the industrial DSM model uses a stochastic net load composed of three terms. It is thus more prone to error and more likely requires more

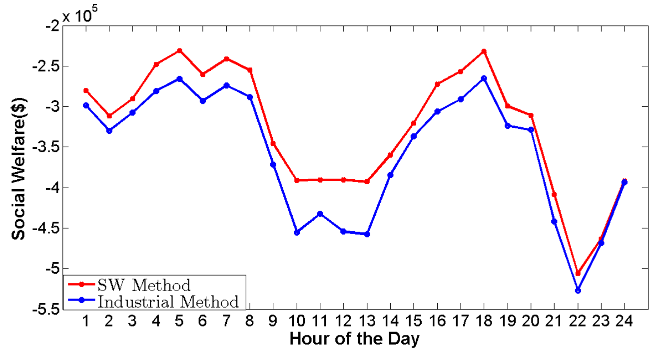

Fig. 2. Social Welfare of SW & Industrial Model

control activity in subsequent layers of enterprise control [45]–[47]. The two DSM models also mitigate the stochastic net load in fundamentally different ways and incentivize greater participation under very different conditions of renewable energy integration and conventional demand.

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