

## IMPACTS OF INDUSTRIAL BASELINE ERRORS ON COSTS & SOCIAL WELFARE IN THE DEMAND SIDE MANAGEMENT OF DAY-AHEAD WHOLESALE MARKETS

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### ABSTRACT

*Demand Side Management (DSM) has been recognized for its potential to counteract the intermittent nature of renewable energy, increase system efficiency, and reduce system costs. While the popular approach among academia adopts a social welfare maximization formulation, the industrial practice compensates customers according to their load reduction from a predefined electricity consumption baseline that would have occurred without DSM. This paper is an extension of a previous paper studying the differences between the industrial & academic approach to dispatching demands. In the previous paper, the comparison of the two models 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 including the additional baseline term. That work showed that the academic and industrial optimization method have the same dispatch result in the absence of baseline errors given the proper reconciliation of their respective cost functions. DSM participants, however, and very much unfortunately, are likely to manipulate the baseline in order to receive greater financial compensation. This paper now seeks to study the impacts of erroneous industrial baselines in a day-ahead wholesale market context. Using the same system configuration and mathematical formalism, the industrial model is compared to the social welfare model. The erroneous baselines is shown to result in a different*

*and more importantly costlier dispatch. It is also likely to require more control activity in subsequent layers of enterprise control. Thus an erroneous baseline is likely to increase system costs and overestimate the potential for social welfare improvements.*

### 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 units
k	index of stochastic generators
l	index of stochastic demand units
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
$P_{GCi}$	dispatched power generation at the $i^{th}$ dispatchable 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  
 $\mathcal{R}_{GCI}$  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  
 $\zeta_{GCj}$  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  
 $\zeta_{DCj}$  utility function constant of the  $j^{th}$  dispatchable demand unit  
 $\mathcal{C}_{DCj}$  cost of the  $j^{th}$  virtual generator  
 $\mathcal{S}_{DCj}$  startup cost of the  $j^{th}$  virtual generator  
 $\mathcal{D}_{DCj}$  shutdown cost of the  $j^{th}$  virtual generator  
 $\mathcal{R}_{DCjt}$  running cost of the  $j^{th}$  virtual generator in the  $t^{th}$  time interval  
 $A_{DCj}$  quadratic cost function coefficient of the  $j^{th}$  virtual generation  
 $B_{DCj}$  linear cost function coefficient of the  $j^{th}$  virtual generation  
 $\xi_j$  cost function constant of the  $j^{th}$  virtual generation

$w_{GCI}$  binary variable for the state of the  $i^{th}$  dispatchable generator in the  $t^{th}$  time interval  
 $u_{GCI}$  binary variable for the startup state of the  $i^{th}$  dispatchable generator in the  $t^{th}$  time interval  
 $v_{GCI}$  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  $j^{th}$  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  
 $\omega_{DCjt}$  binary variable for the state of the  $j^{th}$  virtual generation in the  $t^{th}$  time interval  
 $\mu_{DCjt}$  binary variable for the startup state of the  $j^{th}$  virtual generation at the beginning of the  $t^{th}$  time interval  
 $\nu_{DCjt}$  binary variable for the shutdown state of the  $j^{th}$  virtual generation at the beginning of the  $t^{th}$  time interval

## 1 INTRODUCTION

Demand Side Management (DSM) offers a means for customers to alter their electricity consumption in response to dynamic market prices [1–4], thus providing dispatchable resources from the demand side in addition to the traditional dispatchable generation [5, 6]. DSM has been recognized for its ability to mitigate the fluctuating effects of renewable energy and increase bulk electric grid reliability by load shedding during especially challenging hours [7–9]. The potential benefits of DSM include increasing system efficiency and reducing system cost by peak load shaving [10, 11]. Dispatchable demand participate in meeting the system power balance and reduce the need for expensive generators with high ramping capability, which are likely to be idle during off-peak hours, thus reducing the facility cost of renewable integration [12]. The economic benefits from load reductions are distributed among the electricity supply side, load reducing customers and non-load-reducing customers [13–15]. Independent System Operators (ISOs) and Reliability Transmission Organizations (RTOs) advocate DSM programs to lower market prices, reduce price volatility, improve customer options, and increase price elasticity in both wholesale & retail markets [16]. Several industrial DSM programs are active as a result of the recent deregulation of electricity markets [17–21].

The industrial and academic research on DSM has addressed the maximization of customer utility, the minimization of customer discomfort, and the stabilization of electricity prices [22–28]. The industrial and academic literature propose different methods and goals for DSM implementations. The most adopted method among academic research is to maximize the net benefit from electricity consumption and generation [25, 27–30]. On the other hand, industrial practice uses historical data to predict a baseline of the electricity consumption that would have occurred

without DSM [31–33]. Load reductions from this predefined baseline are treated as “virtual generation” and compensated accordingly [18, 19, 34–37].

A recent paper has numerically shown that despite having dissimilar optimization programs, these two methods yield the same dispatch result provided that 1.) the utility function of dispatchable demand and the cost function of virtual generation are properly reconciled and 2.) the industrial baseline is the same as the load forecast [38]. While the first condition is likely achievable the latter is not. Firstly, the methods of determining the load forecast and industrial baseline are fundamentally different. While the latter is calculated a day in advance based upon sophisticated methods [39], the formulae for baseline are much more basic and determined months in advance [16, 40–43]. Indeed, it is conceivable that a baseline is set and then the demand side participant makes (static) long-term energy efficiency improvements and then is compensated for the now guaranteed “load-reduction”. As several authors note, the baseline itself is subject to manipulation because DSM participants have greater awareness of their facilities than the regulatory agencies charged with estimating the baseline [44, 45]. While the errors associated with the baseline have often been a part of policy discussions [44], they have not been rigorously studied. This paper aims to rigorously study the effects of an erroneous industrial baseline in a day-ahead wholesale market context in terms of dispatch level, social welfare and system cost. Using the same system configuration and mathematical formalism, the dispatch result from industrial model is compared to that from the social welfare model in the presence of baseline error.

The remainder of this paper develops in five sections. Section 2 summaries highlights from both the academic literature and industrial documents, with emphasis on the sources of errors associated with industrial baselines. In Section 3, the mathematical formulation for the social welfare and industrial methods off unit commitment with dispatchable demands are reconciled. The text case and methodology are presented in Section 4. Section 5 presents and discusses the results and conclusions from the case study for social welfare model and industrial model with an erroneously high baseline. The paper concludes in Section 6.

## 2 Background

This section provides highlights from the social welfare method often used in academia as well as the virtual generation method implemented in industry.

### 2.1 Academic Literature

The demand side management dispatch schedule is jointly determined by suppliers and customers [25]. The simplest form of social welfare maximization is often mentioned in power systems textbooks [46] and commonly used in academic research. Assuming an economic dispatch context, the social welfare is

defined as the net benefit from electricity consumption and generation [46]:

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

where  $U$  and  $C$  represent the demand utility and the generation cost,  $P_D$  and  $P_G$  represent the individual power demand and generation levels, and  $m$  and  $n$  represent the number of demand and generator units respectively. The system is subject to power balance constrain which in the simple case is assumed to have zero transmission loss [46].

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

### 2.2 Industrial Practice

In the industrial implementation, each curtailment service provider (CSP) is administratively assigned an electricity consumption baseline by adjusting historical data from the previous year to consider several considerations of the current year such as offset in the day of week [16]. In a hybrid electricity market, the CSP can participate in any of several wholesale energy markets. The Day-Ahead Scheduling Reserve Market (DASR) is one of these. Here, generation suppliers, load serving entities, and CSPs bid together [47], and the ISOs/RTO simultaneously allocates the dispatchable resources and determines the whole-sale electricity price such that the total cost of dispatchable generation and virtual generation are minimized [37]. Load reductions accepted in day-ahead bidding are penalized for failing to commit [14].

While very much discouraged, customers have an implicit incentive to surreptitiously inflate the administrative baseline for greater compensation. For example, the customers can artificially increase their electricity consumption when baselines are being evaluated [44]. Customers who anticipate to reduce loads regardless of DSM are also more likely to be attracted to participate [44]. Another example is customers having multiple facilities shift loads between facilities to create false load reductions [44]. Successful baseline manipulation may cause generation relocation and inefficient price information [44].

## 3 Mathematical Models

This section describes the mathematical formulation for the social welfare and industrial virtual generation models. For consistency of research methodology, the provided models are the same as those in the prequel to this work [38].

### 3.1 Social Welfare Maximization

Unlike the economic dispatch model in Section 2.1, the unit commitment problem in this work schedules the dispatchable re-

sources over multiple time intervals and determines their states during each time interval. The model also adds stochastic generation (i.e. renewable energy) and stochastic demand (i.e. conventional load) to the optimization program. The goal of the optimization remains to maximize social welfare over all time intervals. Here, it is implemented as the minimization of the negative social welfare. 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 objective function for the negative of social welfare  $\mathcal{W}$  is given by [38]:

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

where both the generation cost  $\mathcal{C}_{GCi}$  and demand utility  $\mathcal{U}_{DCj}$  are composed of a startup, a shutdown, and a running component shown in Equation (4) and Equation (5) [38].

$\forall i = 1, \dots, N_{GC}, j = 1, \dots, N_{DC}, \forall t = 1, \dots, T :$

$$\begin{aligned} \mathcal{C}_{GCi}(P_{GCit}) = \\ u_{GCit}(\mathcal{S}_{GCi}) + v_{GCit}(\mathcal{D}_{GCi}) + w_{GCit}[\mathcal{R}_{GCi}(P_{GCit})] \end{aligned} \quad (4)$$

$$\begin{aligned} \mathcal{U}_{DCj}(P_{DCjt}) = \\ u_{DCjt}(\mathcal{S}_{DCj}) + v_{DCjt}(\mathcal{D}_{DCj}) + w_{DCjt}[\mathcal{R}_{DCj}(P_{DCjt})] \end{aligned} \quad (5)$$

where the running cost for generators  $\mathcal{R}_{GCit}$  and running utility for demands  $\mathcal{R}_{DCjt}$  are modeled as quadratic functions to describe the change in marginal costs and marginal utilities with increasing level of dispatchable generation and dispatchable demand respectively [38]:

$$\begin{aligned} \mathcal{R}_{GCi}(P_{GCit}) = A_{GCi}(P_{GCit})^2 + B_{GCi}(P_{GCit}) + \zeta_{GCi} \\ \mathcal{R}_{DCj}(P_{DCjt}) = A_{DCj}(P_{DCjt})^2 + B_{DCj}(P_{DCjt}) + \zeta_{DCj} \end{aligned} \quad (6)$$

The social welfare maximization is subject to several constraints:

- system power balance (Equation (7)),
- capacities of the dispatchable generators and demands units (Equation (8 & 9)),
- ramping limits of the dispatchable generators and demand units (Equation 10 & 11),
- the logical relations for the dispatchable generators & demand units (Equations 12 & 13) [38].

$$\begin{aligned} \forall t = 1, \dots, T \\ \sum_{i=1}^{N_{GC}} P_{GCit} - \sum_{j=1}^{N_{DC}} P_{DCjt} = \sum_{k=1}^{N_{DS}} \hat{P}_{DSkt} - \sum_{l=1}^{N_{GS}} \hat{P}_{GSlt} \end{aligned} \quad (7)$$

$$w_{GCit} * \underline{P_{GCi}} \leq P_{GCit} \leq w_{GCit} * \overline{P_{GCi}} \quad (8)$$

$$w_{DCjt} * \underline{P_{DCj}} \leq P_{DCjt} \leq w_{DCjt} * \overline{P_{DCj}} \quad (9)$$

$$\begin{aligned} R_{GCit} = P_{GCit} - P_{GCi(t-1)} \\ \underline{R_{GCi}} \leq R_{GCit} \leq \overline{R_{GCi}} \end{aligned} \quad (10)$$

$$\begin{aligned} R_{DCjt} = P_{DCjt} - P_{DCj(t-1)} \\ \underline{R_{DCj}} \leq R_{DCjt} \leq \overline{R_{DCj}} \end{aligned} \quad (11)$$

$$w_{GCit} = w_{GCi(t-1)} + u_{GCit} - v_{GCit} \quad (12)$$

$$w_{DCjt} = w_{DCj(t-1)} + u_{DCjt} - v_{DCjt} \quad (13)$$

### 3.2 Industrial Practice: Cost Minimization with Demand Baseline

The industrial unit commitment model schedules all dispatchable resources like the social welfare model, but is different in that it minimizes the total cost of dispatchable and virtual over all time intervals of the SCUC period (Equation 14) [38]. The cost of virtual generation is defined as the compensation paid to the customers for reducing their consumption from a predefined demand baseline.

$$\sum_{t=1}^T \left[ \sum_{i=1}^{N_{GC}} \mathcal{C}_{GCi}(P_{GCit}) + \sum_{j=1}^{N_{DC}} \mathcal{C}_{DCj}(\tilde{P}_{DCjt} - P_{DCjt}) \right] \quad (14)$$

where the costs of the dispatchable generation has been defined in Equation (4) and the costs of dispatchable demand shown in Equation (15) also have startup, shutdown, and running cost [38].

$$\begin{aligned} \forall i = 1, \dots, N_{GC}, \forall t = 1, \dots, T \\ \mathcal{C}_{DCj}(\tilde{P}_{DCjt} - P_{DCjt}) = \\ \mu_{DCjt}(\mathcal{S}_{DCj}) + v_{DCjt}(\mathcal{D}_{DCj}) + \omega_{DCjt}[\mathcal{R}_{DCj}] \end{aligned} \quad (15)$$

The running cost mirrors that of the dispatchable generation and is modeled as a quadratic function of virtual generation or the load reduction from the baseline [38].

$$\begin{aligned} \mathcal{R}_{DCj}(\tilde{P}_{DCjt} - P_{DCjt}) = \\ \Delta_{DCj}(\tilde{P}_{DCjt} - P_{DCjt})^2 + \mathbb{B}_{DCj}(\tilde{P}_{DCjt} - P_{DCjt}) + \xi_{DCj} \end{aligned} \quad (16)$$

The total cost minimization is subject to same system power balance constraint (Equation 7), capacity limits (Equations 8) &

17), ramping limits (Equations 10 & 11), and logical constraints (Equations 12 & 18) for dispatchable generators and dispatchable demands.

$$\forall j = 1, \dots, N_{DC}, \forall t = 1, \dots, T$$

$$\omega_{DCjt} * \tilde{P}_{DCjt} - P_{DCjt} \leq \tilde{P}_{DCjt} - P_{DCjt} \quad (17)$$

$$\tilde{P}_{DCjt} - P_{DCjt} \leq \omega_{DCjt} * \tilde{P}_{DCjt} - P_{DCjt}$$

$$\bar{w}_{DCjt} = \bar{u}_{DCj(t-1)} + \bar{u}_{DCjt} - \bar{v}_{DCjt} \quad (18)$$

### 3.3 Model Reconciliation

The virtual generation cost function in the industrial model is reconciled with the utility function of the corresponding dispatchable demand unit such that the loss in utility in the SW model is equal to the change in virtual generation cost. 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 [38].

$$-\mathcal{U}_{DCj}(P_{DCj}) + \mathcal{U}_{DCi}(P_{DCj} + \delta P_{DCj}) =$$

$$\mathcal{C}_{DCj}(\tilde{P}_{DCj} - P_{DCj}) - \mathcal{C}_{DCj}(\tilde{P}_{DCj} - P_{DCj} - \delta P_{DCj}) \quad (19)$$

Rearranging quadratic and linear terms in Equation (19) yields Equation (20) [38]. It shows that the cost function of load reduction is dependent on the choice of baseline.

$$\mathbb{A}_j = -A_j$$

$$\mathbb{B}_j = 2 * A_j * \tilde{P}_{DCj} + B_j \quad (20)$$

That the stochastic net load line in the social welfare and industrial DSM models are different is an important observation [38]. In the social welfare model, it is composed of two terms

$$\sum_{k=1}^{N_{DS}} \hat{P}_{DSkt} - \sum_{l=1}^{N_{GS}} \hat{P}_{GSl t}$$

In the industrial model, it is composed of the same two terms plus a third

$$\sum_{k=1}^{N_{DS}} \hat{P}_{DSkt} - \sum_{l=1}^{N_{GS}} \hat{P}_{GSl t} + \sum_{j=1}^{N_{DC}} \tilde{P}_{DCjt}$$

In the case where the industrial baseline is subject to gaming, it is reasonable to conclude that the stochastic netload line in the industrial DSM model is more error prone than its social welfare counterpart.

The two models are now ready to be compared in the presence of baseline errors with a specific case.

## 4 Case Study Methodology

The case study uses the same test case as the prequel to this work [38]. It consists of a day-ahead unit commitment simulation in a wholesale market for both the social welfare and industrial DSM methods. For fairness of comparison, the two models

use the same system configuration and data. The results are studied in terms of dispatched energy resources, resulting social welfare, and total system costs. Data is drawn from the *Reliability Test System(RTS)-1996* [50, 51] and the Bonneville Power Administration (BPA) website [48, 49]. The following subsections describe the simulation parameters in detail.

### 4.1 Time Scale

In the study of a day-ahead UC program, a 1-hour time interval is chosen for a total time span of 24 hours.

### 4.2 Stochastic Generation, Stochastic Demand, & Demand Baseline

The stochastic generation in this case is the renewable energy generation. Only the aggregated renewable generation is necessary in the power balance constraint equation. It is drawn from the wind forecast data published on the Bonneville Power Administration (BPA) website for May 12, 2013 [49]. To have the load better suit the dispatchable energy resources in the simulation, the data was scaled up to 1.6 times of its value. The raw data for the load forecast has a sampling resolution of 5 minutes and was down sampled by taking hourly averages. The resulting numbers are provided in Table 1.

Similarly, the stochastic demand is taken as the conventional load. Its aggregate value is drawn from the BPA load repository for the same day [48], scaled by the same factor, and downsampled to an hourly resolution. The resulting numbers are provided in Table 1 and only apply to the demand side units not participating in the DSM program.

For the sake of simplicity, a dispatchable demand unit was assumed to exist on each bus. This work sets the true baseline to a time-invariant value equal to 9.6% of the peak demand published for that bus in the RTS-1996 test case. Furthermore, this work assumes this error-free baseline is equal to the maximum capacity of the dispatchable demand unit in the social welfare model.  $\tilde{P}_{DCj} = \bar{P}_{DCj}$ . In the industrial model, the erroneous baseline was set to 120% of its true value to emphasize its impact. This has the implicit effect of allowing demand units to have a maximum load reduction (capacity) of 120% as that found in the social welfare model.

### 4.3 Dispatchable Generation & Dispatchable Demands

Dispatchable generators refer to the generation plants that can be fully controlled. Dispatchable demands come from the DSM participants and are assumed to be fully controllable without error.

Dispatchable generator parameters are listed in Table 2 [50]. The startup cost is based on hot start. Slack generators, regulating generators and hydro generators do not participate in unit

**TABLE 1.** Stochastic Demand and Generation Levels in MW [48, 49]

Hour of the Day	1	2	3	4	5	6	7	8	9	10	11	12
Load Forecast 05/15/2013 (MW)	8347	8036	7795	7691	7711	7827	7994	8487	9186	9515	9626	9648
Wind Forecast 05/15/2013 (MW)	3163	2528	2518	2861	3037	2878	3231	3576	3320	3242	3471	3335
Hour of the Day	13	14	15	16	17	18	19	20	21	22	23	24
Load Forecast 05/15/2013 (MW)	9679	9618	9594	9621	9657	9701	9728	9753	9927	9753	9132	8498
Wind Forecast 05/15/2013 (MW)	3343	3623	4009	4522	4716	5028	4360	4253	3412	2421	2136	2160

**TABLE 2.** Dispatchable Generator Parameters [50, 51]

$N_{GC}$	72										
Unit Type	Generator Index	$\overline{P_{GCi}}$ (MW)	$P_{GCi}$ (MW)	$\overline{R_{GCi}}$ (MW/MI)	$R_{GCi}$ (MW/MI)	$\zeta_{GCi}$ (\$)	$B_{GCi}$ (\$/MW)	$A_{GCi}$ (\$/MW <sup>2</sup> )	$S_{GCi}$ (\$)	$D_{GCi}$ (\$)	
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	0.1	5750	0	
U155	21,22,31,32,54,55,64,65,87,88,97,98	155	31.0	3	-3	210.4	11.0	0.1	611	0	
U197	45,46,47,78,79,80	197	39.4	3	-3	315.1	21.9	0.01	10189	0	
U350	33,66,99	350	70.0	4	-4	181.0	11.0	0.01	4500	0	
U400	23,24,56,57,89,90	400	80.0	20	-20	343.7	5.6	0.01	4700	0	

**TABLE 3.** Dispatchable Demand Unit Parameters

index	$\overline{P_{DCj}}$ (MW)	$\overline{R_{DCj}}$ (MW/h)	$R_{DCj}$ (MW/h)	$\zeta$ (\$)	$B_j$ (\$/MW)	$A_j$ (\$/MW <sup>2</sup> )	$S_{DCj}$ (\$)	$D_{DCj}$ (\$)
j	0	$\overline{P_{DCj}}/1.6$	$-\overline{P_{DCj}}/1.6$	0	112.5	-0.5	0	0

commitment, and therefore are excluded from the table. 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 3. The minimum and maximum capacity limit of each dispatchable demand unit is assumed to be zero and 9.6% of the peak load at the corresponding bus. It is assumed that each dispatchable demands needs 96 minutes to fully ramp between zero and maximum consumption. For simplicity, no load recovery is considered because the customers are assumed to 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 fairness of comparison, the startup and shutdown costs are neglected (i.e. set to zero) in this case study.

#### 4.4 Computational Methods

The optimization is implemented with MATLAB interfaced with GAMS. Raw data was imported and processed in MATLAB and passed onto GAMS. GAMS runs the optimization problem using CPLEX as the optimization engine since all optimization problems are mixed integer quadratic convex programs. A relative tolerance of 0.0000001 was chosen for all optimization problems to ensure convergence. It takes approximately 1000 seconds to run each optimization program on a desktop computer with Intel(R) Xeon(R) E5405 @ 2.00GHz processor.

#### 5 Results & Discussion

The two demand side management optimization programs are studied for their dispatch levels, social welfare values, and total system costs. The industrial DSM program is subjected to an inflated industrial baseline which is absent from the social welfare model.

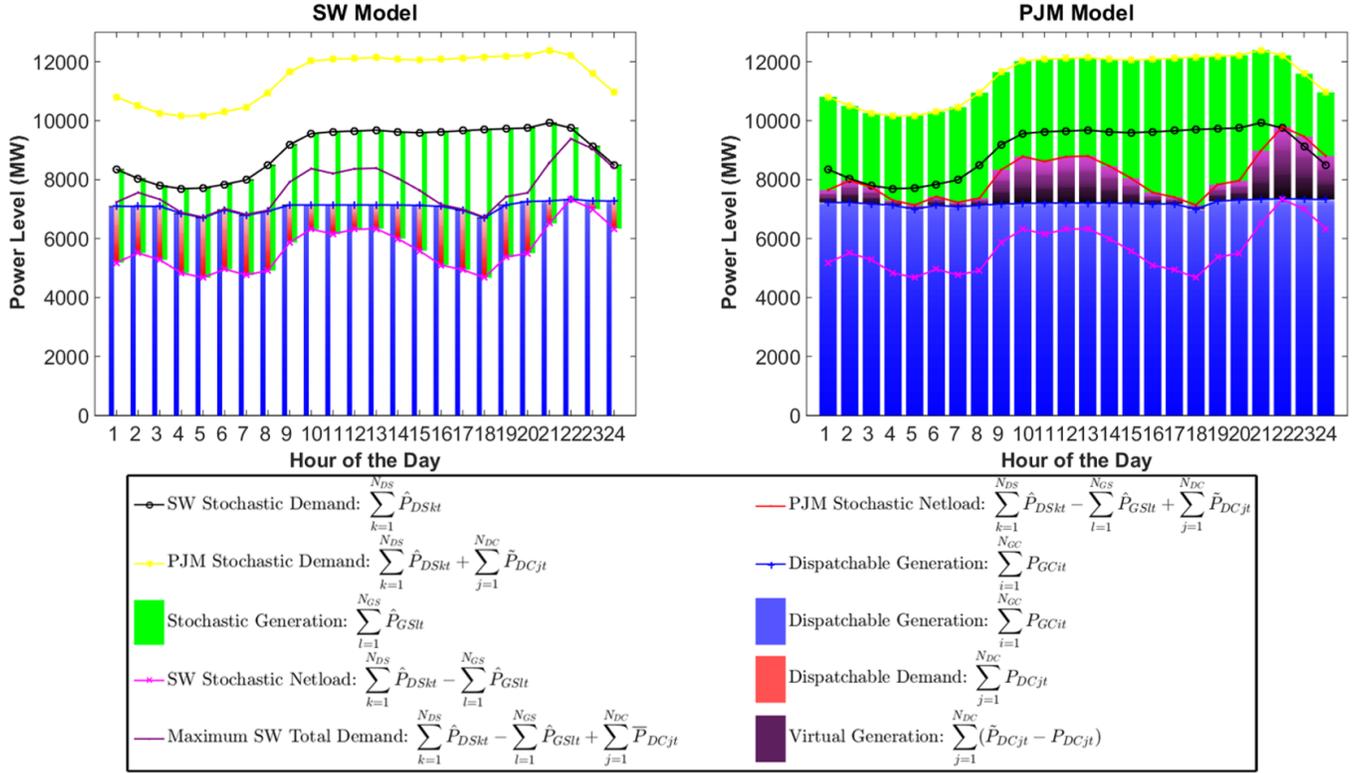


FIGURE 1. Social Welfare & Industrial DSM Model Unit Commitment with Over Estimated Baseline

## 5.1 Dispatch Levels

Figure 1a and 1b show the dispatch levels of the social welfare and industrial optimization respectively. The solid black line represents the non-participating stochastic demand level. Subtracting the stochastic generation from it gives the magenta line: the stochastic net load line in the social welfare model. The purple line in the social welfare model represents the frontier of all the dispatchable demand units consumed at their maximum level.

The mechanics of the industrial DSM model is entirely different. The solid black line still represents the non-participating stochastic demand level. The solid yellow line adds the now artificially inflated dispatchable demand baseline to the black line. 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 purple must meet this line to achieve power system balance. Interestingly, the magenta line now represents the frontier of all the virtual generators at their maximum load reduction (i.e. virtual generation).

Looking at both the social welfare and industrial dispatch in Figure 1. The dispatched generation line appears to remain around 7000MW for much of the day. In the meantime, the dispatchable demand and virtual generation vary substantially from nearly zero to approximately 2000MW over the course of the

day. The industrial dispatchable generation (blue line) in Figure 1b becomes fairly constant compared to that from social welfare model in Figure 1a. This is because the artificially inflated baseline gives the illusion of dispatchable demand levels that may not be achievable in reality, thus requiring more subsequent control.

Returning to the social welfare dispatch in Figure 1a, there is a limit to the ability the DSM can mitigate the sudden loss of renewable energy. For example, in Hour 22, the high stochastic netload from low renewable generation must be met by the generation, and no dispatchable demands are online. On the other hand, in Hour 5 & 18, all the dispatchable demands are running at maximum capacity. Without greater DSM participation, the abundant renewable energy generation are under-utilized.

Industrial DSM dispatch in Figure 1b displays a similar behavior during renewable energy down-ramp events. In Hour 22, while all the virtual generation are running at maximum capacity, the dispatchable generation still needs to rise to meet power balance. However in Hour 5 & 18, the industrial model shows that the virtual generation participate in maintaining a relatively constant dispatchable generation level. This is because the model assumes higher DSM participation than actually exists.

## 5.2 Social Welfare

Figure 2 evaluates the social welfare function ( $-\mathcal{W}$ ) for both simulations. As expected, the hourly social welfare value is highest in Hours 17-20 when the stochastic generation is high and 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. Interestingly, and perhaps unintuitively, the industrial model with artificially high baseline results in “higher” social welfare values. Because the virtual generators are starting from the inflated baseline, their marginal costs accumulate more rapidly than if they had started from the true baseline. As a result, they end up demanding more as measured from zero. This artificially inflates the social welfare function perhaps beyond what is achievable. For example, in the case that the virtual generators are dispatched between 0 and 20% of the baseline, then they are being dispatched to demand *more* than the original load forecast or correct baseline value. This yields a higher social welfare value but does not have a basis in reality.

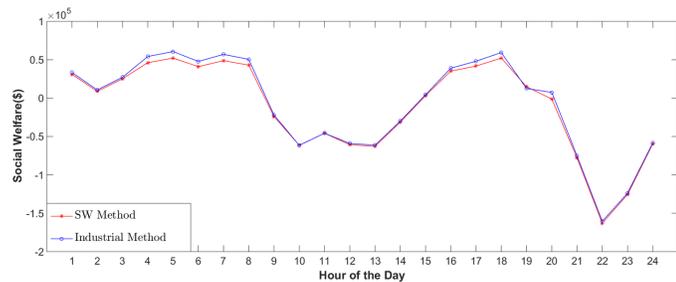


FIGURE 2. Social Welfare Values for the Social Welfare & Industrial Model

## 5.3 System Costs

Figure 3 now evaluates the total system cost function in Equation 14 and compares the results in a similar way. While the industrial model cost is evaluated using an inflated baseline, the social welfare model evaluates the total system cost from an error-free baseline. As expected, the cost from the industrial model is consistently higher than that from the social welfare model because it is compensating for false load reductions. The total costs for the social welfare and industrial models were  $4.45 \times 10^6$  and  $5.12 \times 10^6$  respectively. Thus, in this case the 20% error in industrial baseline lead to a 14.9% difference in the total costs.

## 6 Conclusion

The divergent approaches to Demand Side Management in industrial & academic literature have been contrasted in the pre-

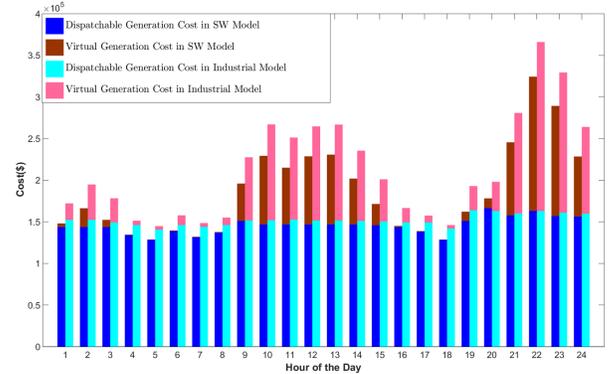


FIGURE 3. System Cost in Social Welfare & Industrial DSM Models

quel to this work [38]. The comparison of the two models 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 including an additional term for the electricity consumption baseline. It is thus more prone to error because customers have the potential to artificially inflate this baseline to gain higher financial compensation for load reduction. This work has compared the two models while introducing a 20% error in industrial electricity consumption baseline. The comparison showed that the errors in baseline lead to different dispatch levels, higher systems costs, and potentially unachievable levels of social welfare. Furthermore, the erroneous baselines is also likely to require more control activity after commitment in subsequent layers of enterprise control [52–56].

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