Impacts of Industrial Baseline Errors in Demand Side Management Enabled Enterprise Control

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Abstract*—Despite the recognized importance of demand side management (DSM) for mitigating the impact of variable energy resources and reducing the system costs, the academic and industrial literature have taken divergent approaches to DSM implementation. The prequel to this work has demonstrated that the inflation of the net load baseline forecast, used by the industrial unit commitment formulation, leads to higher and costlier day-ahead scheduling of dispatchable resources compared to the academic method. Consequently, these baseline inflation errors have to be corrected in the downstream enterprise control activities at faster time scales, increasing the control efforts and reserve requirements for the real-time market dispatch and regulation service. This paper compares the two DSM approaches and quantifies the technical impact of industrial baseline errors in subsequent layers of control using an enterprise control methodology. The adopted enterprise control simulator encompasses three interconnected layers: a resource scheduling layer composed of a security-constrained unit commitment (SCUC), a balancing layer composed of a security-constrained economic dispatch (SCED), and a regulation layer. Baseline error is absent in the social welfare model. The simulations with the industrial model are run for different baseline error levels. The baseline inflation is assumed to have the same effects in the day-ahead and real-time market. The resulting implications of baseline errors on power grid imbalances and regulating reserve requirements are tracked. It is concluded that with the same regulating service, the introduction of baseline error leads to additional system imbalance compared to the social welfare model results, and the imbalance amplifies itself as the baseline error increases. As a result, more regulating reserves are required to achieve the same satisfactory system performance with higher baseline error.

NOMENCLATURE

i, j, l, k, t	indices of dispatchable generators, dispatchable demand units, buses, lines, and time
N_{GC}	Number of dispatchable generators
N_{DC}	Number of dispatchable demand units
N_B	Number of buses
T_{ED}	real-time market time step
$\Delta\mathcal{W}_t$	incremental social welfare at time t
$\Delta\mathcal{U}_{DCjt}$	incremental utility of the j^{th} dispatchable demand unit at time t
$\Delta\mathcal{C}_{DCjt}$	incremental cost of the j^{th} virtual generator at time t
$\Delta\mathcal{C}_{GCit}$	incremental cost of the i^{th} dispatchable generator at time t
A_{DCj}, B_{DCj}	quadratic and linear utility function coefficients of the j^{th} dispatchable demand unit
$\mathbb{A}_{DCj}$, $\mathbb{B}_{DCj}$	quadratic and linear cost function coefficient j^{th} virtual generation
A_{GCi}, B_{GCi}	quadratic and linear cost function coefficient of the i^{th} dispatchable generator
P_{DCjt}, ΔP_{DCjt}	dispatched and incremental power consumption at the j^{th} dispatchable demand unit at time t
$\tilde{P}_{DCjt} - P_{DCjt}$	dispatched power generation at the j^{th} virtual generator at time t
P_{GCit}, ΔP_{GCit}	dispatched and incremantal power generation at the i^{th} dispachable generator at time t
ΔP_{lt}, ΔD_{lt}	dispatchable generation and dispatchable demand increments on bus l at time t
$\Delta\hat{D}_{lt}$	stochastic demand forecast increments on bus l at time t
$\underline{P_{DCj}}$, $\overline{P_{DCji}}$	min. & max. capacity of the j^{th} dispatchable demand unit
$\underline{P_{GCi}}$, $\overline{P_{GCi}}$	min. & max. capacity of the i^{th} dispatchable generator
$\underline{\underline{\tilde{P}_{DCj} - P_{DCj}}}$	min. capacity of the j^{th} virtual generator
$\overline{\tilde{P}_{DCj} - P_{DCj}}$	max. capacity of the j^{th} virtual generator
$\underline{R_{DCj}}$, $\overline{R_{DCj}}$	min. & max. ramping capability of the j^{th} dispatchable demand unit
$\underline{R_{GCi}}$, $\overline{R_{GCi}}$	min. & max. ramping capability of the i^{th} dispatchable generator

$\overline{F_k}$	flow limit of line k
F_{kt}	power flow level of line k at time t
M_{li}, M_{lj}	correspondence matrix of dispatchable generator i and dispatchable demand unit j to bus l
γ_{lt}	incremental transmission loss factor of bus l at time t
a_{klt}	bus l generation shift distribution factor to line k

I. Introduction

The industrial and academic literature are taking divergent approaches to DSM implementation. DSM with its ability to allow customers to adjust electricity consumption in response to market signals provides additional dispatchable resources to mitigate the variable effects of renewable energy [1], [2]. Its advantages have been discussed in the context of enhancing electrical grid reliability as well as reducing system costs through peak load shaping and emergency response [3]–[5]. While the 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 [6]–[8], the industrial trend has been to compensate customers for load reductions from baseline electricity consumption [9]–[11]. Such a baseline is defined as the electricity consumption that would have occurred without DSM and is estimated from historical data [12], [13]. Thus, dispatchable demand reductions are also treated as "virtual generators".

Previous work has demonstrated that while the net load in the academic DSM is composed of two terms, the net load in the industrial DSM is composed of three with an additional baseline term and, therefore, introduces additional forecast errors [14]. The work showed the equivalence of the two methods 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 [14]. However, the accuracy of baseline forecast is not likely achievable, since the load forecast is calculated a day in advance based upon sophisticated methods [15], while the baseline calculation involves much more basic formulae and is determined months in advance [16], [17]. Indeed, the customers have an implicit incentive to surreptitiously inflate the administrative baseline for greater compensation, taking advantage of greater awareness of their facilities than the regulatory agencies charged with estimating the baseline [18], [19]. Successful baseline manipulation has been shown to result in higher levels of day-ahead dispatchable resources scheduling and higher costs in the unit commitment problem [20]. As a result, this baseline error have to be corrected in downstream enterprise control activities at faster time scales, likely requiring greater control effort and higher reserve amounts. This paper compares the two approaches of DSM and seeks to quantify the technical impact of baseline error in subsequent control layers using an enterprise control simulator added with a dispatchable demand module.

The enterprise control assessment method for variable energy resource induced power system imbalances has been recently developed based on the concept of enterprise control [21], [22]. It consists within a single package most of the balancing operation functionality found in traditional power systems. In contrast to the extensive integration studies [23]–[25] previous to it, this holistic assessment method is case independent, addresses both physical grid as well as enterprise control process, and is validated by a set of numerical simulations.

The remainder of this paper develops in five sections. Section II summarizes the highlights from the enterprise control methods, as well as the academic and industrial DSM implementation. In Section III, the mathematical formulations are developed and reconciled. The text case and methodology are presented in Section IV. Section V presents and discusses the case study results. The paper concludes in Section VI.

II. Background

This section summarizes the highlights from the enterprise control model, and the two DSM methods.

A. Enterprise Control

The power system enterprise model encompasses three consecutive control layers on top of the physical grid: resource scheduling layer in the form of a security-constrained unit commitment (SCUC), balancing actions in the form of a security-constrained economic dispatch (SCED) and manual actions, and regulation service in the form of automatic generation control (AGC) [21]. Each lower layer operates at a smaller timescale resulting in subsequently smaller imbalances. The SCUC uses the day-ahead net load forecast to schedule generation with a coarse time resolution. The SCED uses the available load following and ramping reserves to re-dispatch generation units in the real-time market using the short-term net load forecast. In the regulation service layer, the available regulation reserves are used to fine-tune the system balance [21].

The variable energy resources (VER) model is characterized by five parameters for systematic establishment of different integration scenarios: penetration level, capacity factor, variability, day-ahead and short-term forecast errors. The penetration level and capacity factor together determine the actual VER output. The day-ahead forecast error is used by the SCUC problem, while the short-term forecast error is an input to the SCED problem. Variability measures the changing rate of VER [21].

Readers are referred to [21] for detailed description of each control layer and the formal definitions of the five parameters listed above. References [21], [25], [26] include the definitions of reserve types, namely load following and ramping reserves used in the real-time market, and the regulation reserve used in the regulation service.

B. Social Welfare vs Industrial DSM

The simplest form of the social welfare maximization from [27] is commonly used in academic research. Elastic demand is characterized by its utility, that is the benefit from electricity consumption, and generation is characterized by its cost [27]. The optimization determines the electricity prices and setpoints for all dispatchable resources simultaneously to maximize the net benefits [6].

Much like the social welfare model, the DSM dispatch schedule and price are jointly determined by suppliers and consumers [6] to minimize the total cost of the dispatchable and virtual generations. 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. Accepted load reductions are subsidized by ISO/RTO. Customers have an implicit incentive to surreptitiously inflate the administrative baseline for greater compensations, and successful baseline manipulation may cause generation relocation and inefficient price information [18].

III. Model Development

This section describes the SCUC & SCED mathematical models with dispatchable demand units for both DSM methods and the reconciliation between the two models.

A. Social Welfare Model

The social welfare UC optimization program with dispatchable demand has been described in detail in the prequel to this paper [14]. In the real-time market, the SCED moves the available dispatchable generation and demand units to new setpoints based on the short-term net load forecast. In contrast to the SCUC, the SCED problem runs at each real-time dispatch time step and determines the changes in power levels for one point at a time. Also, the SCED does not make decisions on the on/off states. Inclusion of transmission configuration is necessary. Some input parameters depend on the current state of the system, and are calculated prior to each SCED iteration based on a full AC power flow analysis of the system [21]. The optimization goal is to maximize incremental social welfare, formulated as the first derivative of the social welfare function:

$$\Delta \mathcal{W}_t = \sum_{j=1}^{N_{DC}} \Delta \mathcal{U}_{DCjt} - \sum_{i=1}^{N_{GC}} \Delta \mathcal{C}_{GCit} \tag{1}$$

where

$$\Delta \mathcal{U}_{DCjt} = B_{DCj} \Delta P_{DCjt} + 2A_{DCj} P_{DCjt} \Delta P_{DCjt} \tag{2a}$$

$$\Delta \mathcal{C}_{GCit} = B_{GCi} \Delta P_{GCit} + 2A_{GCi} P_{GCit} \Delta P_{GCit} \tag{2b}$$

subject to power balance constraint in (3).

$$\sum_{l=1}^{N_B} (1-\gamma_{lt})(\Delta P_{lt} - \Delta D_{lt} - \Delta \hat{D}_{lt}) = 0 \tag{3}$$

where

$$\Delta P_{lt} = \sum_{i=1}^{N_{GC}} M_{li} \Delta P_{GCit}, \quad \Delta D_{lt} = \sum_{j=1}^{N_{DC}} M_{lj} \Delta P_{DCjt} \tag{4}$$

The incremental transmission loss factor (ITLF) γ_{jt} for bus j shows how much the total system losses change when power injection on bus j increases by a unit [28]. Line flow limits are shown in (5). The generation shift distribution factor (GSDF) a_{klt} shows how much the active power flow through line k changes when injection on bus l increases by a unit [28], [29]. Additional constraints include capacity limits for dispatchable demand and generation units in (6 & 7), and ramping limits for dispatchable demand and generation units in (8 & 9) respectively.

$$\sum_{l=1}^{N_B} a_{klt} (\Delta P_{lt} - \Delta D_{lt} - \Delta \hat{D}_{lt}) \leq \overline{F_k} - F_{kt} \tag{5}$$

$$P_{DCjt} - \underline{P_{DCj}} \leq \Delta P_{DCjt} \leq \overline{P_{DCji}} - P_{DCjt} \tag{6}$$

$$P_{GCit} - \underline{P_{GCi}} \leq \Delta P_{GCit} \leq \overline{P_{GCi}} - P_{GCit} \tag{7}$$

$$\underline{R_{DCj}} * T_{ED} \leq \Delta P_{DCj} \leq \overline{R_{DCj}} * T_{ED} \tag{8}$$

$$\underline{R_{GCi}} * T_{ED} \leq \Delta P_{GCi} \leq \overline{R_{GCi}} * T_{ED} \tag{9}$$

B. Industrial Model with Baseline

The industrial UC optimization program integrating dispatchable demand has been described in detail in [14]. Much like the SW model, the industrial SCED optimizes for one point of time and includes transmission losses. The optimization goal is to minimize the total incremental cost, formulated as the first derivative of the cost function:

$$\sum_{i=1}^{N_{GC}} \Delta \mathcal{C}_{GCit} + \sum_{j=1}^{N_{DC}} \Delta \mathcal{C}_{DCjt} \tag{10}$$

where the dispatchable generation incremental costs remain the same and

$$\Delta \mathcal{C}_{DCjt} = -\mathbb{B}_{DCj} \Delta P_{DCjt} - 2\mathbb{A}_{DCj} P_{DCjt} \Delta P_{DCjt} \tag{11}$$

The optimization is subject to the same power balance constraint in (3) and line flow limits in (5), capacity limits for virtual and dispatchable generation units in (12 & 7), and ramping limits for virtual and dispatchable generation units in (8 & 9) respectively.

$$(\tilde{P}_{DCjt} - P_{DCjt}) - \underline{\tilde{P}_{DCj} - P_{DCj}} \leq -\Delta P_{DCjt} \tag{12a}$$

$$-\Delta P_{DCjt} \leq -\overline{\tilde{P}_{DCj} - P_{DCj}} - (\tilde{P}_{DCjt} - P_{DCjt}) \tag{12b}$$

C. Model Reconciliation

The same model reconciliation in [14] is adopted. Namely

$$\mathbb{A}_j = -A_j, \quad \mathbb{B}_j = 2 * A_j * \tilde{P}_{DCj} + B_j \tag{13}$$

IV. Case Study Methodology

This section describes the testcases and methodology used in this paper.

A. Testcase & Simulation Data

1) Timescales: The SCUC simulation runs at the beginning of the 24 hour time span and has 1-hour time step. The SCED and regulation run over the course of the day and have time steps of 5 minutes and 1 minute respectively.

TABLE I
STOCHASTIC LOAD & GENERATION PARAMETERS

	Penetration Level	Capacity Factor	Variability	Day-Ahead Forecast Error	Short-Term Forecast Error
Load	-	-	1	0.01	0.01
Wind	0.2	1	1	0.05	0.05

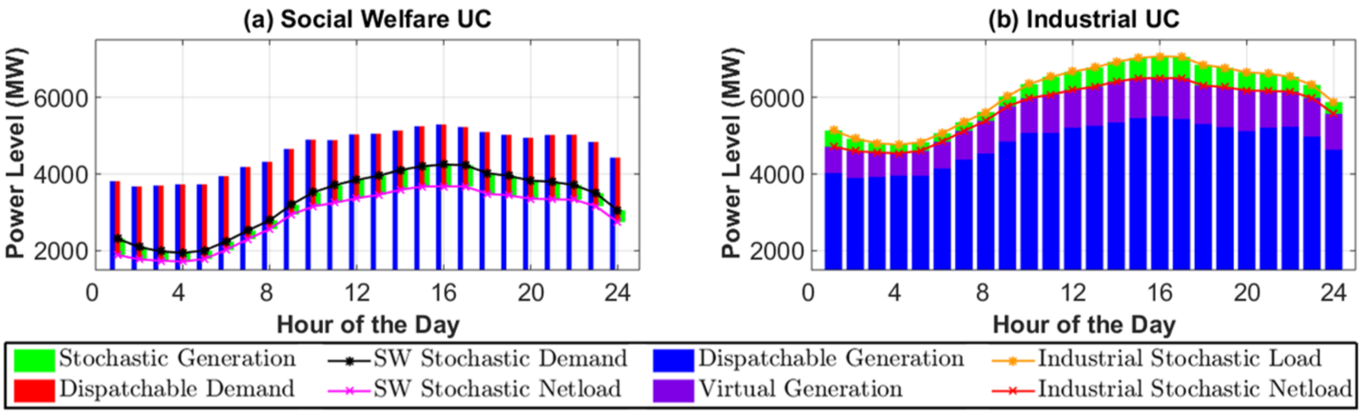

Fig. 1. SCUC

2) Dispatchable Generation & Dispatchable Demand: The IEEE RTS-96 (Reliability Test System-1996) is used as the physical grid configuration [30], which is consisted of 99 generators, 73 busses and $8550MW$ of peak load. An adequate load-following reserve is set to 20% of the peak load to allow good load-tracking in the real-time market. This ensures that the regulating service is mostly utilized to offset the residual imbalances from the real-time market.

In this work, each aggregated dispatchable demand is assumed to occur at each bus. In the social welfare model, the minimum and maximum capacity limits of each dispatchable demand unit is assumed to be zero and 9.6% of the peak load at the corresponding bus. The utility function coefficients for all dispatchable demand units are assumed to be equal and time-invariant. In the industrial model, an accurate baseline equals the maximum capacity of the dispatchable demand in the social welfare model. The baseline inflation error is assumed to be the same in both energy markets. Simulations are run for different baseline error levels. The startup and shutdown costs of dispatchable demand units and virtual generators have entirely different physical meanings in the social welfare and industrial DSM models and are set to zero for fairness of comparison.

3) Stochastic Load & Stochastic Generation: Load and wind daily profiles are taken from Bonneville Power Administration (BPA) repositories with 5 minutes resolution [31], [32]. The raw data are up-sampled to a 1-minute resolution using *sinc* functions to avoid distortions in the power spectrum [33]. The load and wind parameters are tabulated in Table I.

B. Computational Method

The simulator is implemented with MATLAB interfaced with GAMS. While the UC problem is carried out in GAMS using CPLEX for mixed integer quadratic constraint (MIQCP) programs, the rest of simulations including testcase setup, linearized economic dispatch, regulation and power flow analysis are performed in MATLAB. One day simulation lasts 196 seconds with Inter(R) Core(TM) i7-4600 CPU @ 2.10GHz on 8.00GB RAM, showing a 20% increase in time with the addition of dispatchable demands.

V. RESULTS & DISCUSSION

This section shows the scheduling from day-ahead unit commitment and real-time economic dispatch. At various regulating reserves levels, the system imbalances are tracked for social welfare model and at different baseline errors for the industrial model.

A. Day-Ahead Dispatch Levels

Figure 1 compares the SCUC by both methods. Figure 1(a) shows the social welfare optimization. The difference between the stochastic demand from non-participating customers (solid black line) and the wind generation (green bars) gives the stochastic net load in the social welfare model (magenta line). The dispatchable generation in blue bars meets the sum of stochastic net load in magenta line and dispatchable demand in red bars. Figure 1(b) shows the industrial UC with a 10% baseline error. The solid orange line shows industrial stochastic demand including load from non-participating customers and baseline load from DSM participants. The subtraction of the wind generation in green bars from the orange line gives the red line: the industrial stochastic net load. It is met by the sum of dispatchable generation in blue bars and virtual generation in purple bars. In both models, ramping of dispatchable resources occurs at the first five minutes of each hour.

Comparing 1(a)&(b), it is observed that the baseline inflation results in erroneously high dispatchable and virtual generation. The excess dispatchable generation will be offset

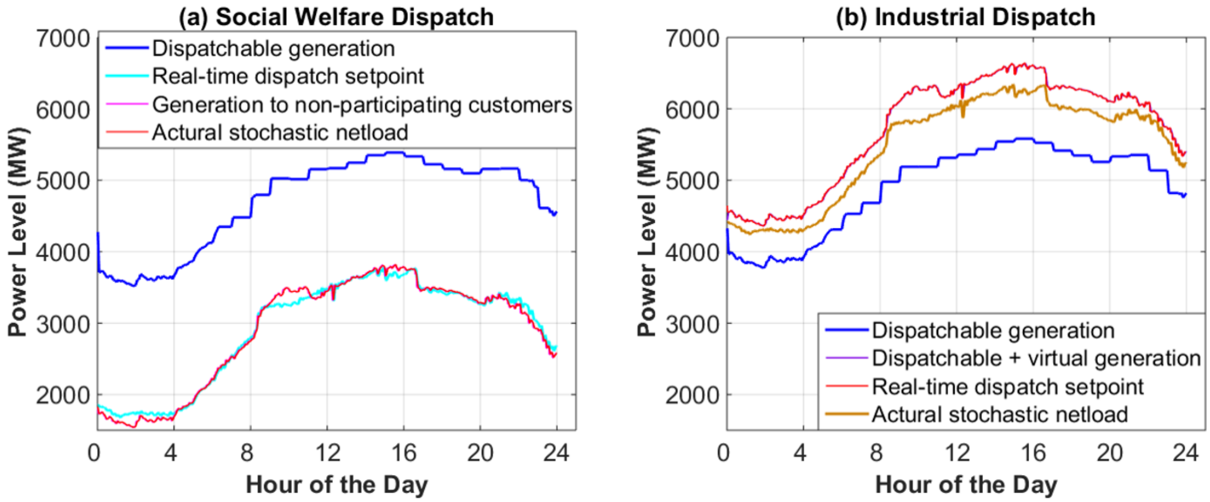

Fig. 2. SCED

in real-time economic dispatch given enough load-following reserves, and otherwise further carried over to regulation layer.

B. Dispatch Levels in Real-Time

It should be emphasized that Figure 2 shows SCED results at 1-minute sampling rate, but has implications from SCUC and regulation layers, since SCED only dispatches units decided online by UC, and regulation participates in system balancing. The relationship of subtracting wind generation from stochastic load gives the stochastic net load is straightforward, and is not demonstrated.

Figure 2(a) shows social welfare SCED. The magenta line shows the set-point for meeting stochastic net load, and is the net result from stochastic netload and compensation for previous imbalances. The solid blue line represents the dispatchable generation. Subtracting the dispatchable demand consumption from this blue line gives the red line: the generation allocated to the stochastic demand from the non-participating customers. The magenta and red line coincide very five minutes at each real-time dispatch, indicating adequate load following reserves. The actual real-time net load is then represented by the solid cyan line. The deviation between the setpoint and the actual net load is mainly due to the stochastic load and wind forecast error.

Figure 2(b) shows the real-time dispatch of the industrial model with a 10% baseline error. The solid blue line represents the dispatchable generation. The purple line shows the sum of dispatchable and virtual generation. The solid red line represents the set-point of total generation, and is determined from the the sum short-term industrial stochastic net load forecast and the imbalance at previous dispatch. Again the red and purple line meet at dispatch time points, indicating adequate load-following reserves. Now interestingly comes the actual industrial stochastic net load represented by the brown line with no baseline error. The huge deviation between the set-point and the actual net load is mostly due to the baseline error, in addition to the stochastic load and wind forecast error.

C. System Imbalance vs. Regulating Reserves

In Figure 3, each curve plots the averaged absolute system imbalance against the regulating reserves where both quantities are normalized against the peak load. The absolute imbalance is summed over all buses to represent the total system imbalance at each specific time point. This quantity is then averaged at a one-minute sample rate over the day to evaluate the system performance. As expected, better system performance is observed at greater regulating reserve amount for all scenarios. The blue line shows the system imbalance from social welfare model, and in other words, no baseline errors. The system has a 0.68% averaged imbalance without regulating services, and drops below 0.02% after the reserve reaches 5% of peak load. The orange, yellow, purple, and green line represents industrial model with 1%, 2%, 5%, and 10% respectively. At zero regulating service, they have 0.74%, 0.8%, 1.4%, and 2.9% averaged system imbalance, which drops below 0.02% after the regulating reserve is increased to 6%, 6%, 8%, and 11% respectively.

Generally speaking, higher system imbalances are associated with larger baseline errors. In the social welfare model where the dispatch is free from baseline errors, the system is still subject to load and wind forecast errors. In the industrial model, the introduction of baseline forecast exacerbates the overall forecast error. The imbalance in the case with 1% baseline error is comparable to that in the social welfare model when the error is relatively small compared to the other forecast errors. The imbalance increases rapidly as the baseline error is raised to 5% and 10%. Unfortunately as explained in the introduction, the baseline forecast is likely to have low accuracy and the cases with high imbalance are likely to occur.

VI. Conclusion

This paper compares the academic and industrial DSM implementations using a recently developed enterprise control model added with a dispatchable demand module. The baseline introduces one more forecast quantity and therefore higher forecast errors to the industrial model. The baseline errors result in erroneously high dispatch levels in both the day-ahead and real-time markets, and the error is then carried over to the regulation layer. Higher system imbalances are induced by higher baseline errors, which requires greater regulation reserves amount to achieve the same satisfactory system performance.

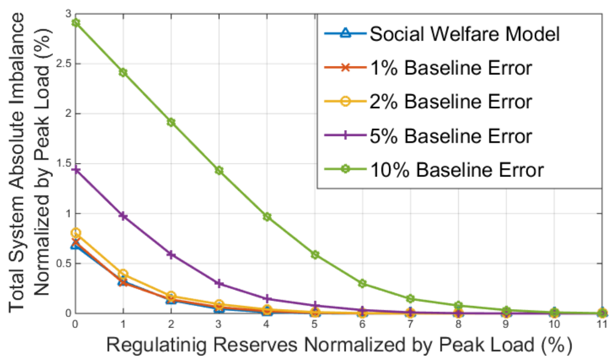

Fig. 3. System Imbalances vs. Regulating Reserves

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