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A DDDAMS FRAMEWORK FOR REAL-TIME LOAD DISPATCHING IN POWER NETWORKS

Aristotelis E. Thanos
Xiaoran Shi
Juan P. Sáenz
Nurcin Celik

Industrial Engineering
University of Miami
Coral Gables, FL 33146 USA

ABSTRACT

The economic environmental load dispatch problem in power networks aims at producing electricity at the lowest financial and environmental costs. In this paper, we propose a novel real-time dynamic data driven adaptive multi-scale simulation framework (RT-DDDAMS) for efficient real-time dispatching of electricity. The framework includes 1) a discovery procedure where the network is split into sub-networks and prospective fidelities are identified, 2) an RT-DDDAMS platform involving algorithms for state estimation, fidelity selection, and multi-objective optimization alongside with a system simulation; and 3) databases for storing sub-network topologies, fidelities, and selective measurements. The best compromise load dispatch obtained from this framework is then sent to the considered power network for deployment. The proposed framework is illustrated and validated via a modified IEEE-30 bus test system. The experiments reveal that the proposed framework significantly reduces the computational resource usages needed for the reliable power dispatch without compromising the quality of the solutions.

1 INTRODUCTION

The goal of the economic and environmental load dispatch (EELD) is to produce electricity at the lowest cost and emissions to reliably serve customers, while recognizing the operational limits of generation plants and transmission lines (Energy Policy Act 2005; Zhang et al. 2005). The dispatching of loads is performed to control and allocate the total energy generation amongst the available resources (including both conventional and renewable sources) within a power network.

Environmental and economic load dispatching for power networks is a challenging task due to several reasons. First, power networks are highly dynamic and complex in their nature due to the variability in their status induced by different sources of energy generation and their associated generation capacities, environmental emissions, frequency of changes in load profiles, market policies and regulations, and revenues generated, amongst many others (Sáenz et al. 2013). Second, power networks may operate at various scales and scopes, causing the range for the solution space to be considerably large. Third, the inclusion of renewable energy into power systems, which is expected to increase significantly in the near future, has resulted in additional constraints on EELD such as more unpredictable ramp rates and the need for additional reserves to accommodate the intermittent nature of the output. Furthermore, this dynamicity and complexity inherent to these problems enforce significant burden on the available computational resource utilization while the developed solution procedures are being deployed, even if they are performed at specified intervals or offline. This burden further frustrates the monolithic implementation of the methodologies presented in the literature (Abido 2009; Colson and Nehrir 2009) in a realistic setting and necessitates a distributed framework for effective decision making within these systems.

Addressing the challenges mentioned above, in this study, we investigate a novel real-time dynamic data driven adaptive multi-scale simulation framework (RT-DDDAMS) for the efficient and reliable real-time dispatching of electricity under uncertainty. The proposed framework includes 1) a discovery procedure, in which the topology of the power network is explored and split into sub-networks to guide the RT-DDDAMS with a predetermined set of simulation fidelities, 2) three databases storing data regarding sub-network topologies, fidelities, and selective measurement involving electrical and environmental sensor data, 3) an algorithm for online state estimation of the demand nodes in the considered electrical grid and a data driven simulation platform for mimicking the system response behavior, 4) an algorithm for fidelity selection in simulation considering the trade-off between the computational requirements of simulations, and accuracy of anticipated dispatch results in terms of environmental and economic costs, and 5) a multi-objective optimization algorithm for generating a dispatch configuration which minimizes the total monetary and environmental cost of the system, without posing security risks to the energy network.

The rest of the paper is organized as follows. In Section 2, we provide the background and literature review on dynamic data driven application systems (DDDAS) paradigm. In Section 3, we describe our proposed RT-DDDAMS framework for economic and environmental load dispatching in electricity networks. In Section 4, we evaluate the performance of the proposed framework using experimental cases based on a modified version of the IEEE-30 bus system. Finally in Section 5, we provide conclusions and discuss the future venues for this work.

2 PREVIOUS WORKS ON DDDAMS PARADIGM

The dynamic data driven application systems (DDDAS) paradigm has been extensively studied in the literature during the past decade. The motivation behind this paradigm resides in two major incidents that took place in January and May of 2000: 1) a missed prediction of the track and magnitude of a major storm by meteorologists, which blanketed major cities from South Carolina to New England, and 2) a failure to simulate what the behavior of the fire near the Los Alamos National Laboratory and to take the appropriate actions to limit its propagation, respectively (NSF 2000). The DDDAS entails the ability to dynamically incorporate data into an executing application simulation, and in reverse, the ability of applications to dynamically steer the measurement process (Darema 2005). It has been successfully investigated in a variety of application areas, such as contaminant tracking (Douglas et al. 2006), natural disaster forecasting (Patrikalakis et al. 2004), social and behavioral cognition (Kim and Heller 2006), biological system prediction (NSF Workshop Report 2006), supply chains (Celik et al. 2010), amongst many others.

Findings of the previous research (Darema 2005; Abido 2009) draw attention to the challenges of automatically adapting simulations when experimental data indicates that a simulation must change. Adaptation to the identified change typically starts with an initial procedure to obtain an overall insight regarding the phenomenon of interest. This insight is then utilized to determine the origins of abnormalities within the considered system and sample observations from areas of critical interest. Based on the information acquired at the sampling stage, the presented application models are structurally or operationally updated to reflect this knowledge in an automated and timely manner.

Generalizing software to anticipate all the possible ways a phenomenon could change is difficult, and attempting to do so usually comes at the expense of performance, and furthermore, makes simulation code unmanageably complex (Parnas 1979). However, this limitation for software adaptation can be resolved by taking advantage of the flexibilities and constraints of a simulation simultaneously. On one hand, automatic adaptation is impossible without flexibility, since there is no way to know which alternatives should be considered. On the other hand, there are too many alternatives to consider in a timely fashion if the constraints are not considered, thereby leading to the infeasibility of the process. Therefore, Carnahan and Reynolds (2006) propose a semi-automated adaptation approach that exploits the flexibility and constraints of model abstraction opportunities to automate simulation adaptation. While their study does not contain manual or automatic interference of the code or application of optimization methods which can make the software extremely complex to control, it is still in need of human intervention to determine the most likely places of the code that require a change. In our proposed research, changes in level of detail of data acquisition and the choice of certain parameters over others allow the automatic multi-fidelity adaptation in the simulation model. While the use of real-time simulation as a task generator is common ground for these works as well as for our current study, the adaptive fidelity selection and ranking scheme that guides the RT-DDDMAS is novel in our work. The proposed fidelity selection mechanism allows for significant reduction in the computational resource utilization while keeping the model accurate by wisely selecting the most appropriate fidelity for the system simulations.

3 PROPOSED RT-DDDAMS FRAMEWORK

In order to address the challenges mentioned in Section 1, in this study, we propose a real-time dynamic data driven adaptive multi-simulation (RT-DDDAMS) framework. The proposed framework is overviewed in Figure 1. The overall scheme envisioned is a robust multi-scale federation of simulation models that enables efficient and optimal power dispatch in power networks.

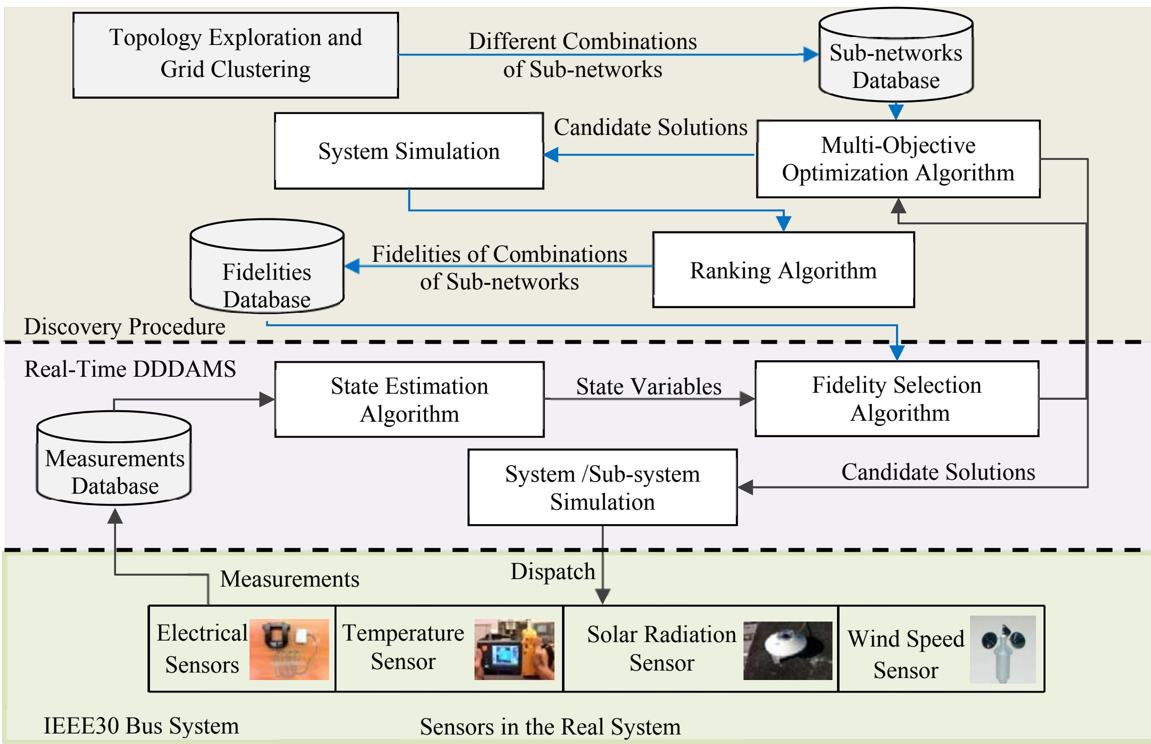


Figure 1: Overview of the proposed RT-DDDAMS framework with embedded databases and algorithms

The proposed RT-DDDAMS framework includes an offline discovery procedure and a real-time DDDAMS decision making procedure. The offline discovery procedure incorporates algorithms for grid topology and clustering, multi-objective optimization, fidelity ranking; and databases for sub-networks and fidelities. The grid topology and clustering algorithm examines the structure of the power network and determines the different possible sub-networks that may be built to compose the full power network.

Based on the results from the topology and clustering algorithm, the different sub-networks and their combinations are used to generate power dispatch solutions under various predetermined load scenarios. Performances of these power dispatches are evaluated based on the best-compromise solution generated for each of the sub-network combinations in terms of their costs and emissions. Then, for each of the different load scenarios, the combinations are ranked using fuzzy logic.

The RT-DDDAMS framework embodies a measurements database that is fed using electrical and environmental sensors. Given the sensory data and available computational resources, a state estimation algorithm, and a fidelity selection algorithm are invoked to determine the state of the system and fidelity that the simulation should be performed at. Based on the estimated system status and the selected fidelities, a multi-objective optimization algorithm is employed to generate a non-dominated solution set in terms of costs and emissions. Then, a best compromise solution is selected and sent to the actual power network for realization. The details of the components embedded in the proposed framework are presented in the following sub-sections.

3.1 Multi-Objective Optimization Algorithm

The proposed RT-DDDAMS framework is employed to provide the considered power network with the best possible solution, which is the environmental and economic load dispatch (EELD) in this case. Because of the multi-objective nature of the EELD problem, a multi-objective optimization algorithm is incorporated into the proposed framework. In this section, the details of the algorithm are presented.

3.1.1 Formulation of the EELD Problem

The EELD problem has two distinct objectives, namely, minimizing the generation costs and minimizing the pollutant emissions of a power network's load dispatch while acknowledging the system's limitations. The problem is formulated in equations (1) through (7), where the decision variables are the real (P_G) and reactive (Q_G) power produced at each generation bus. Equations (1) and (2) present the cost and emissions objectives, where, a_i, b_i and c_i are cost coefficients, N_G is the number of generating units, P_{G_i} and Q_{G_i} are the real power and reactive power generated, and α_i, β_i, γ_i, ϵ_i and μ_i are the emissions coefficients.

$$Minimize\ F(P_G) = \sum_{i=1}^{N_G} a_i + b_i P_{G_i} + c_i P_{G_i}^2 \tag{1}$$

$$Minimize\ E(P_G) = \sum_{i=1}^{N_G} [10^{-1}\left(\alpha_i + \beta_i P_{G_i} + \gamma_i P_{G_i}^2\right) + \epsilon_i e^{\mu_i P_{G_i}}] \tag{2}$$

The constraints of the problem are presented in equations (3)-(7). Equation (3) represents the generation capacity constraint which ensures that all energy generating plants operate within their capacity. Equations (4)-(7) represent the power balance constraints which ensure that the load provided to the system meets the demand while taking energy transmission losses into account.

$$P_{G_i}^{min} \leq P_{G_i} \leq P_{G_i}^{max} \qquad \forall_i \tag{3}$$

$$\sum_{i=1}^{N_G} P_{G_i} - P_D = P_{loss} \tag{4}$$

$$P_{G_i} - P_{D_i} - V_i \sum_{j=1}^{N_B} V_j [G_{ij} cos\left(\delta_i - \delta_j\right) + B_{ij} sin(\delta_i - \delta_j)] = 0 \qquad \forall i \tag{5}$$

$$Q_{G_i} - Q_{D_i} - V_i \sum_{j=1}^{N_B} V_j [G_{ij} sin\left(\delta_i - \delta_j\right) + B_{ij} cos(\delta_i - \delta_j)] = 0 \qquad \forall i \tag{6}$$

$$P_{loss} = i \sum_{i=1}^{N_G} g_k [V_i^2 + V_j^2 - \cos\left(\delta_i - \delta_j\right)] \tag{7}$$

Here, $P_{G_i}^{min}$ and $P_{G_i}^{max}$ are the minimum and maximum operating output of unit i, respectively, N_B is the number of buses, P_{D_i} and Q_{D_i} represent the real and reactive loads at bus i, V_i is the voltage magnitude at bus i, G_{ij} is the transfer conductance between buses i and j, δ_i is the voltage angle at bus i, B_{ij} are the transfer conductance and susceptance between bus i and bus j, g_k is the conductance of the k^{th} line.

Given the formulation of the EELD problem, in the next subsection, we present the formulation of the multi-objective optimization algorithm embedded into our proposed framework.

3.1.2 Multi-Objective Optimization using Particle Filtering Algorithm

Celik et al. (2012) propose a multi-objective optimization algorithm by extending a particle filtering based optimization framework into multi-objective optimization problems. The EELD optimization problem described in Section 3.1.1, may be alternatively represented by (8) and (9), where $x, m,$ and x^* are the decision vector, number of decision variables, and Pareto optimal solution set, respectively. Furthermore, $f_1(x)$ and $f_2(x)$ represent equations (1) and (2), respectively.

$$x^* = arg\ min\ f(x) = arg\ min\left(f_1(x), f_2(x)\right) \tag{8}$$

$$x = (x_1, x_2, \ldots, x_m) \in R^m \tag{9}$$

The state space model defined for the particle filtering based multi-objective optimization is provided in (10) and (11), and the importance density function is defined in (12). In these equations, $x_k = (x_{k,1}, x_{k,2}, \dots, x_{k,m})$ is the state of the system at time k, $y_k = (y_{k,1}, y_{k,2}, \dots, y_{k,n})$ is the measurement taken at time k, $v_k = (v_{k,1}, v_{k,2}, \dots, v_{k,n})$ is the measurement noise distributed with a pdf $\varphi(\cdot)$.

$$x_{k+1} = x_k, \tag{10}$$

$$y_k = f(x_k) - v_k, \tag{11}$$

$$q_k(x_k) = \frac{\varphi(f(x_k)-y_k)q_{k-1}(x_k)}{\int \varphi(f(x_k)-y_k)q_{k-1}(x_k)dx_k} \tag{12}$$

The algorithm is based on a particle filtering procedure that includes two-sampling stages. In the first stage, samples are taken from within the non-dominated solution set generated by the algorithm. In the second stage, a sampling distribution is generated using the solutions with the best performance in each of the separate objectives, and then samples are drawn from this distribution. The number of samples, an empty non-dominated set, and the number of iterations, are defined as the algorithm's input. Once initialization is completed, the data for buses, lines, and cost are used for random sampling. The admittance matrix is then updated to reflect the distributed generation levels from the random dispatch, and the resulting loads and the equivalent resistance are calculated. In the next step, the resultant power generation as well as the energy transmission losses is evaluated, and the dispatch at the swing bus is adjusted to ensure the power balance constraints are met. Then the non-dominated solution set is calculated and the resampling stage is triggered. The new samples obtained from the resampling at each distribution level are then used to update the admittance matrix sequentially. Once the predefined number of iterations is reached, the final non-dominated solution set is calculated and the corresponding objective values are exported.

3.2 Discovery Procedure

In the discovery procedure, the topology of the power network is explored, so that different potential sub-networks are identified, to guide the RT-DDDAMS with a predetermined set of simulation fidelities. This is achieved with a decomposition technique, through which the entire network under consideration is decomposed into n non-overlapping observable sub-networks (Rakpenthai et al. 2005). Furthermore, each of these sub-networks must include at least one source of energy generation. Once the network is decomposed, the information of all the sub-networks and their combinations is stored into the sub-networks database. The number of items stored in the database is $2^n - 1$, where n is the number of sub-networks.

Once the combinations are defined, demand levels are selected in order to generate different scenarios with which different fidelities will be evaluated. In this step m levels of load variation are selected. Each of the sub-networks is mapped to a load with a variation corresponding to each of the m levels, so that the permutation of the levels within the sub-networks generates the number of different scenarios. At this point it is important to highlight that a 0% level is always included within the m levels of load variation, and the simulation is not performed when the demand in all the sub-networks is at this level; thus the total number of scenarios is $(m^n - 1)$. Based on the number of sub-network combinations and levels, the total number of simulations performed by the discovery procedure is $(2^n - 1)(m^n - 1)$.

It should be noted that the selection of the demand levels have a significant role in the accuracy of the proposed framework. On one hand, if few but very different levels of load variation are selected, the predetermined fidelities may not provide a good approximation for the demand variations of the real-time simulation. On the other hand, if many but close levels are selected, the accuracy of the fidelity selection obtained for the power dispatch may be optimal. However, because of the permutation involved in the generation of scenarios, the discovery procedure becomes unrealistic in the latter.

A set of non-dominated solutions is generated for each of the $(2^n - 1)(m^n - 1)$ simulations based on cost and emissions. They are then ranked for each of the $(2^n - 1)$ sub-networks for each of the $(m^n - 1)$ scenarios, based on best compromise solution, using fuzzy logic. Finally, the rankings are saved into the fidelities database.

3.3 State Estimation Algorithm

The real-time state estimation algorithm for computing the electricity demand is triggered by measurements obtained from the sensors in the real system via the interaction with the sub-networks and fidelities databases. Efficient state estimation is crucial in this study since it significantly affects the control of the power flow, fidelity selection, security of the system, and performance of the load dispatch. To this end, in our proposed RT-DDDAMS paradigm, accurate estimates of real-time electricity demands are obtained via a smart sampling algorithm whose seeds were planted in their earlier work (i.e., Thanos and Celik, 2013). The demand is estimated at the distribution level from smart sampling perspective using two sub-procedures whose operations are explained below.

3.3.1 Sub-procedure I

The goal of the first sub-procedure is to estimate the real and reactive power injections of the considered electricity network using environmental measurements (i.e., temperature readings), to incorporate the environmentally-driven impacts. To be specific, during cold days, temperature increments lead to a decrease in the electricity demand, due to reduced heating demands, while on hot days, these temperature increments increase the electricity consumption due to higher cooling demands. To this end, the state-space model for electricity demand estimation in the first sub-procedure is given in equations (13) and (14).

$$D_{k+1} = \alpha D_k + U \tag{13}$$

$$D_k = \beta T_k + V \tag{14}$$

where D_{k+1} and D_k are the posterior state (i.e., demand), current state T_k is the current temperature, α and β are parameters related to state evolution and observation functions that are statistically calculated from historical data, and U and V represent the process noises and measurement errors, respectively.

3.3.2 Sub-procedure II

For the purpose of modifying the minor variation of the estimates and increasing the estimation accuracy, in the second sub-procedure, the available measurements of the electrical parameters (i.e., voltage magnitudes, power injections, power flow, etc.) are employed. Then, the refined state-space model for this sub-procedure is given in equations (15) and (16) as follows:

$$D_{k+1} = \gamma D_k + U \tag{15}$$

$$D_k = \mu(D_k) z_{k,j} + V, \quad \forall j \in \{1,2,\dots,J\} \tag{16}$$

Here γ is a parameter computed in a way analogous to that of α and β in the first sub-procedure, $\mu(\cdot)$ is a function relating the measurements to the power injection states, and J is the number of different measurements within any corresponding time interval t.

The states of the network are set as the real and reactive power injections of the buses. Data collection frequency (time interval estimation) is determined on the basis of load variation and response times of the available energy resources. The limits of these frequencies are governed by the fastest possible response time of energy resources, and the maximum duration in which the load variation is kept unchanged. Higher frequencies of data collection lead to a higher estimation accuracy and lower frequencies result in lighter computational burdens. Consequently, data collection frequency should be decided considering this trade-off. Once this frequency is determined, the algorithm generates four state variables corresponding to real and reactive power injections for either "weekday" or "weekend day" for each bus. Figure 2 presents the operation of the state estimation algorithm.

3.4 Fidelity Selection Algorithm

The effective culling and fidelity selection algorithm is designed to determine which sub-networks should be included in the RT-DDDAM simulation and which sub-networks' dispatch should remain unchanged. This way, a near optimal dispatch may be attained while ensuring an acceptable computational burden.

Whenever the dispatch of the system is to be updated, either because of periodic revision, or because a large change in the state of the system has been predicted, the fidelity selection algorithm is deployed. If the demand predicted by the state estimation algorithm suggests that the system continues to operate under normal conditions, dispatch results from the simulations running at earlier fidelities can be accepted. However, if a significant variation is detected in any of the loads, the fidelity algorithm is employed to select a new simulation fidelity. Here, for each of the different sub-networks, the algorithm determines load variations within the sub-networks using previous dispatch and current estimated loads. Based on these variations, the algorithm matches each of the sub-network variations to the closest corresponding demand level from the fidelities database. Once all of the sub-networks have been matched, the ranking for the corresponding fidelity is used to determine which sub-networks should be included in the simulation.

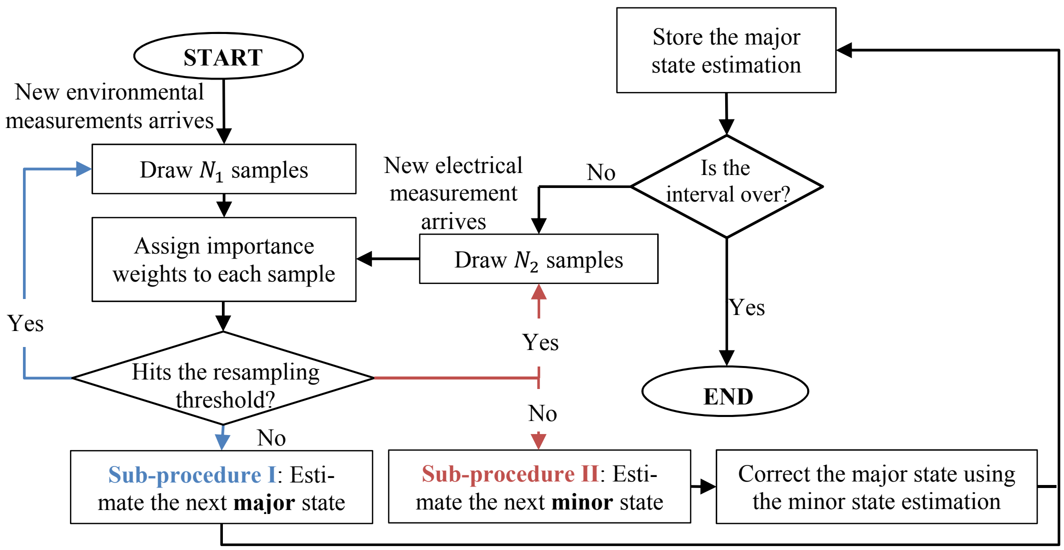


Figure 2: Flowchart of the embedded stated estimation algorithm

Two conditions are utilized to evaluate the ranking from the fidelities database. The first condition excludes combinations where 1) multiple sub-networks are included and 2) more than 90% of all of the networks' generation capacity is included. This condition is included to avoid the use of full system simulations which will incur a large computational burden because of the extensive search space for the optimization. The second condition excludes combinations where the total generation capacity of the sub-networks included is inferior to 10% of the networks' generation capacity. This condition avoids the use of simulations in which diverse solutions meeting the power balance conditions cannot be obtained due to the narrow search space. The solutions that have been avoided by the second condition, not only would have a large computational burden, but also would provide a very limited non-dominated solution set.

4 EXPERIMENTS AND RESULTS

4.1 Modified IEEE-30 Bus Systems

In order to demonstrate the validity of the proposed RT-DDDAMS framework in real-time load dispatching problems, a set of experiments are carried out based on a modified IEEE-30 bus system. The original IEEE-30 bus system consists of 30 buses and 41 lines; these buses consist of 6 generation buses, 19 load buses, and 5 buses that neither generate nor request electricity. As mentioned in section 3.2, the network is divided into 3 sub-networks according to Rakpenthai et al. (2005). To this end, 5 sources of distributed generation are added, arbitrarily located at buses 7, 21, 22, 23 and 27 in the modified IEEE-30 bus system, as shown in Figure 3. The data regarding the characteristics of this system is obtained from the Power Systems Test Case Archive of the Department of Electrical Engineering at the University of Washington (2012), and the cost data and generation capacities are obtained from Phonrattanasak (2010).

4.2 Discovery Procedure Simulation

The studied network is split into three sub-networks and three levels of load variation (0%, 5%, and 10%) are selected. Therefore, a total of 182 different simulations were carried out, for 26 scenarios with 7 combinations each. The performances of the simulations are shown in Table 1. The combinations within each scenario are ranked based on linear membership functions that give equal weight for both objectives.

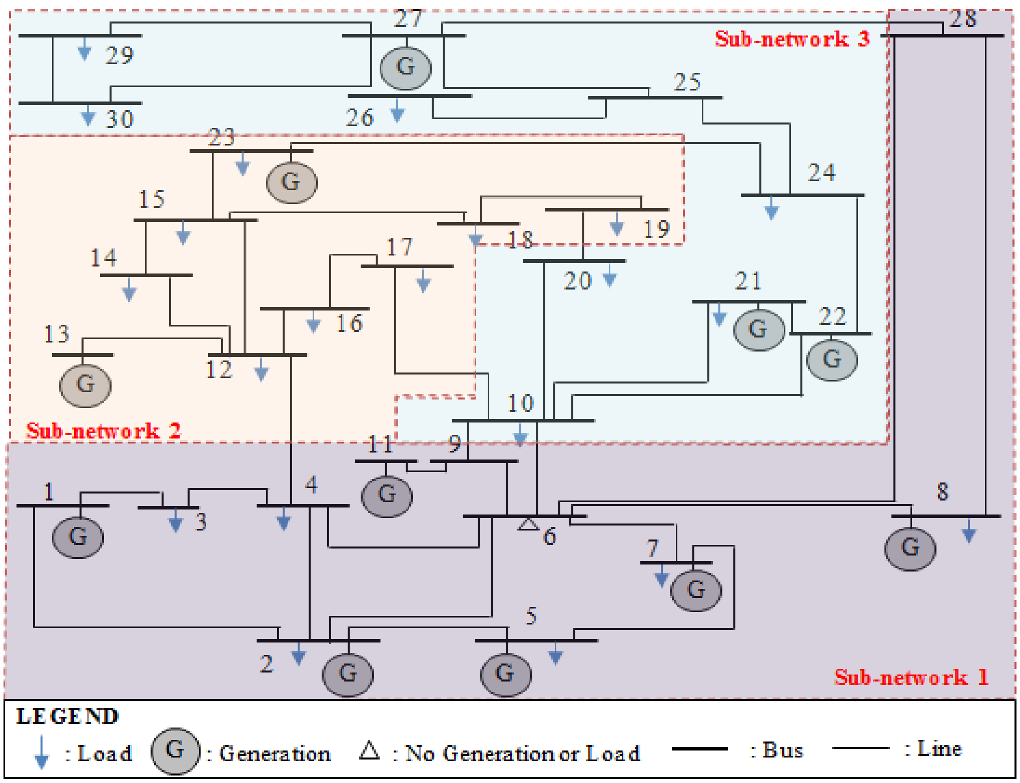


Figure 3: Modified IEEE-30 bus system with three sub-networks

Table 2 presents the scenarios that correspond to different fidelities and ranks, as well as the probability that a certain scenario is given a certain rank. It shows that, on average, the best performing sub-network simulation fidelities are the combinations that include only sub-network 2, only sub-network 3 and sub-networks 2 and 3. These three fidelities are ranked in the top three combinations in 52 of the 78 scenarios. Since the probability of their performances belonging to the top three among all the combinations is close to 70%, they are recommended as the simulation fidelity when the demand variations are difficult or impossible to achieve, or in extreme cases where the demand variations do not adjust to any of the predetermined levels of variation, and the burden of a full system simulation may be avoided. Except for these cases, the fidelities database obtained through the discovery procedure, provided in Table 3, is used as a reference, to search for the most suitable fidelities under different demand variation levels.

4.3 RT-DDDAMS Evaluation

In order to evaluate real-time DDDAMS framework, the state estimation algorithm has been used to generate 10 different cases where the environmental sensory data has been randomly generated.

Table 1: Best compromise solutions from the discovery procedure

Demand Change (%)			Simulated Sub-Networks (All Potential Combinations of Sub-Networks)													
			1		2		3		1,2		1,3		2,3		1,2,3	
1	2	3	Cost	Emission	Cost	Emission	Cost	Emission	Cost	Emission	Cost	Emission	Cost	Emission	Cost	Emission
0	0	5	605.85	0.26730	595.46	0.26730	579.92	0.26733	569.66	0.26736	583.55	0.26732	520.51	0.26744	595.00	0.26732
0	0	10	636.60	0.26725	591.88	0.26731	592.77	0.26730	634.15	0.26726	635.74	0.26726	580.39	0.26733	592.11	0.26732
0	5	0	651.86	0.26724	591.88	0.26731	589.40	0.26731	655.03	0.26723	600.33	0.26729	611.52	0.26727	639.06	0.26726
0	5	5	590.25	0.26730	629.81	0.26724	611.98	0.26727	614.61	0.26728	636.05	0.26723	634.63	0.26723	628.68	0.26724
0	5	10	639.44	0.26723	613.43	0.26727	580.82	0.26733	606.94	0.26727	620.34	0.26725	612.79	0.26727	582.07	0.26733
0	10	0	642.24	0.26724	603.11	0.26728	577.22	0.26733	612.77	0.26728	659.97	0.26723	547.88	0.26739	645.95	0.26726
0	10	5	658.18	0.26723	587.33	0.26731	622.96	0.26725	643.15	0.26723	643.08	0.26724	600.65	0.26729	617.23	0.26726
0	10	10	646.02	0.26723	612.76	0.26727	638.92	0.26722	659.13	0.26722	645.05	0.26721	653.02	0.26719	636.89	0.26724
5	0	0	645.75	0.26722	591.74	0.26731	627.43	0.26724	611.00	0.26726	655.12	0.26722	595.98	0.26730	660.65	0.26722
5	0	5	664.34	0.26720	597.53	0.26729	626.06	0.26724	634.41	0.26724	627.83	0.26724	612.50	0.26727	708.32	0.26718
5	0	10	652.94	0.26720	653.31	0.26719	594.85	0.26730	651.80	0.26721	687.04	0.26718	630.06	0.26724	645.87	0.26722
5	5	0	633.35	0.26724	649.17	0.26720	644.07	0.26721	629.36	0.26724	648.12	0.26720	654.22	0.26719	632.48	0.26724
5	5	5	645.96	0.26721	653.29	0.26719	608.95	0.26727	638.05	0.26721	669.71	0.26717	649.75	0.26720	673.38	0.26719
5	5	10	696.17	0.26717	650.39	0.26720	665.07	0.26717	626.51	0.26725	705.22	0.26716	637.84	0.26722	657.77	0.26722
5	10	0	662.13	0.26719	651.95	0.26720	645.42	0.26721	661.30	0.26719	668.64	0.26719	581.38	0.26732	660.00	0.26718
5	10	5	669.08	0.26718	661.18	0.26718	613.88	0.26726	650.56	0.26719	687.44	0.26717	655.30	0.26719	647.11	0.26720
5	10	10	694.15	0.26715	619.38	0.26725	636.31	0.26722	694.24	0.26716	682.82	0.26716	667.59	0.26717	667.11	0.26718
10	0	0	677.58	0.26717	626.60	0.26724	648.91	0.26720	640.73	0.26721	655.98	0.26719	663.55	0.26718	692.85	0.26719
10	0	5	700.81	0.26715	621.58	0.26725	656.43	0.26719	677.72	0.26718	678.68	0.26717	661.83	0.26718	658.82	0.26718
10	0	10	684.70	0.26715	670.84	0.26716	655.30	0.26719	707.98	0.26715	702.59	0.26712	691.85	0.26713	699.08	0.26714
10	5	0	671.25	0.26717	658.29	0.26719	623.85	0.26725	681.92	0.26718	706.97	0.26715	673.55	0.26716	672.25	0.26717
10	5	5	685.28	0.26714	658.18	0.26719	657.63	0.26719	675.56	0.26717	659.25	0.26718	693.67	0.26712	695.22	0.26714
10	5	10	689.80	0.26714	679.11	0.26715	683.42	0.26714	661.54	0.26718	695.52	0.26714	692.18	0.26713	657.09	0.26718
10	10	0	679.63	0.26714	679.06	0.26715	635.80	0.26723	688.44	0.26714	699.12	0.26713	687.19	0.26714	690.79	0.26715
10	10	5	716.91	0.26710	676.77	0.26715	660.30	0.26718	694.21	0.26714	699.75	0.26711	665.84	0.26717	688.11	0.26713
10	10	10	732.53	0.26710	699.81	0.26711	687.80	0.26713	694.44	0.26712	717.98	0.26710	705.92	0.26710	667.06	0.26716

Table 2: Discovery procedure combination ranking

Combination \ Rank	1	2	3	4	5	6	7
1	1 - 3.8%	2 - 7.7%	2 - 7.7%	2 - 7.7%	5 - 19.2%	11 - 42.3%	3 - 11.5%
2	5 - 19.2%	5 - 19.2%	8 - 30.8%	7 - 26.9%	1 - 3.8%	0 - 0.0%	0 - 0.0%
3	4 - 15.4%	7 - 26.9%	5 - 19.2%	6 - 23.1%	4 - 15.4%	0 - 0.0%	0 - 0.0%
1,2	5 - 19.2%	1 - 3.8%	0 - 0.0%	3 - 11.5%	6 - 23.1%	4 - 15.4%	7 - 26.9%
1,3	5 - 19.2%	2 - 7.7%	1 - 3.8%	1 - 3.8%	4 - 15.4%	8 - 30.8%	5 - 19.2%
2,3	3 - 11.5%	5 - 19.2%	10 - 38.5%	4 - 15.4%	3 - 11.5%	0 - 0.0%	1 - 3.8%
1,2,3	3 - 11.5%	4 - 15.4%	0 - 0.0%	3 - 11.5%	3 - 11.5%	3 - 11.5%	10 - 38.5%

Table 3: Fidelities database

Demand Change (%)			Ranking							Demand Change (%)			Ranking						
1	2	3	1	2	3	4	5	6	7	1	2	3	1	2	3	4	5	6	7
0	0	5	2	1,3	1	3	1,2,3	1,2	2,3	5	5	10	3	2	2,3	1,2	1,2,3	1	1,3
0	0	10	3	2	2,3	1,2,3	1	1,3	1,2	5	10	0	1,2,3	2	3	1,2	2,3	1	1,3
0	5	0	1,3	2,3	3	2	1,2	1	1,2,3	5	10	5	1,2	1,2,3	2	2,3	3	1	1,3
0	5	5	2,3	1	2	1,2,3	3	1,3	1,2	5	10	10	2,3	3	2	1,2,3	1,3	1	1,2
0	5	10	1,2	1,3	2,3	2	3	1	1,2,3	10	0	0	1,3	1,2	3	2,3	2	1	1,2,3
0	10	0	2	3	2,3	1,2	1	1,3	1,2,3	10	0	5	1,2,3	3	2,3	2	1,3	1,2	1
0	10	5	3	1,2,3	2,3	2	1,2	1,3	1	10	0	10	2	3	2,3	1	1,3	1,2,3	1,2
0	10	10	2,3	3	1,3	2	1	1,2,3	1,2	10	5	0	2	3	2,3	1	1,3	1,2,3	1,2
5	0	0	1,2	3	2	2,3	1	1,3	1,2,3	10	5	5	1,3	1	2,3	2	3	1,2	1,2,3
5	0	5	3	2,3	2	1,3	1,2	1	1,2,3	10	5	10	1,2,3	2	2,3	3	1,2	1	1,3
5	0	10	2	2,3	1	3	1,2,3	1,2	1,3	10	10	0	1	2,3	2	3	1,2	1,3	1,2,3
5	5	0	1,3	2	3	2,3	1,2	1	1,2,3	10	10	5	1,3	1,2,3	2	3	2,3	1	1,2
5	5	5	1,2	2,3	2	3	1	1,3	1,2,3	10	10	10	1,2	1,2,3	3	2	2,3	1,3	1

The fidelities selection database has been used by the RT-DDDAMS framework in the fidelity selection and culling algorithm. For each case, the RT-DDDAMS searches for the closest scenario by comparing the estimated demand changes with the three demand change levels. Once the corresponding scenario is identified, simulations are performed for the two top ranked sub-network combinations. This general rule bears two main exceptions that include the simulation of sub-network combinations with all of the sub-networks and the combination with only sub-network 3, as discussed in section 3.4.

In Table 4, the 7 combinations were run and ranked for each of the 10 cases, in order to further evaluate the effectiveness of the proposed RT-DDDAMS framework. T choice of the two fidelities chosen by the RT-DDDAMS can be benchmarked against this ranking.

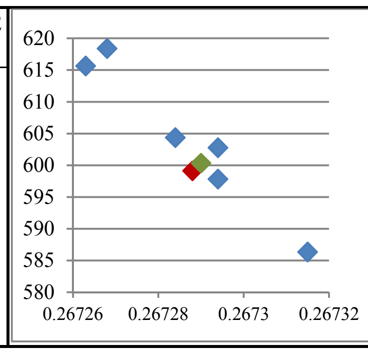
Table 4: Fidelity ranking for the experimental cases

Case	Demand Change (%)			Ranking						
	1	2	3	1	2	3	4	5	6	7
1	0.39	1.50	1.32	1,2,3	2	2,3	1,3	1,2	3	1
2	0.99	0.54	3.77	2	2,3	3	1,2,3	1,3	1	1,2
3	0.32	2.74	2.27	1,2,3	1,3	2,3	1,2	2	3	1
4	3.90	1.69	0.39	1,3	1,2,3	1	2,3	2	3	1,2
5	2.26	0.10	2.60	1,3	1,2	2	1	2,3	3	1,2,3
6	2.55	4.56	6.70	1,3	2,3	2	1	3	1,2,3	1,2
7	5.74	3.48	1.38	1,2,3	2,3	1,3	1,2	3	2	1
8	7.40	0.45	2.28	1,3	2,3	1,2,3	1,2	2	3	1
9	4.50	3.45	12.39	1,2,3	1	2	1,3	3	1,2	2,3
10	10.36	6.24	4.26	2,3	1	2	3	1,2	1,2,3	1,3

Table 5 shows combinations selected by the RT-DDDAMS framework for each of the 10 cases, their rankings, and a comparison between the best sub-network combination obtained through experimental simulation and the suggested fidelity by the RT-DDDMAS for case 3. The table shows that the selected fidelities rank among the top two combinations in five of the cases and among the top three in eight of them. In the figure, blue dots represent experimental compromise solutions for case 3, red dot is the best solution found from the experimental simulations (i.e., combinations of sub-network 1, 2, and 3), and green dot is the result obtained via the suggested simulation 1 (i.e., combinations of 1 and 2). It is shown that the red and green dots are close to each other, meaning that there is no significant difference between the performances of these two combinations. Therefore, it can be concluded that the proposed RT-DDDMAS is able to provide a good compromise solution without utilizing great computational resources.

Table 5: Proposed sub-network simulation configuration from simulation culling

Case	Demand Change (%)			Discovery	Suggested Simulation 1		Suggested Simulation 2	
	1	2	3	Case	Sub-Networks	Rank	Sub-Networks	Rank
1	0.39	1.50	1.32	0,0,0*	1,3	4	2,3	3
2	0.99	0.54	3.77	0,0,5	2	1	1,3	5
3	0.32	2.74	2.27	0,5,0	1,3	2	2,3	3
4	3.90	1.69	0.39	5,0,0	1,2	7	3	6
5	2.26	0.10	2.60	0,0,5	2	4	1,3	1
6	2.55	4.56	6.70	5,5,5	1,2	7	2,3	2
7	5.74	3.48	1.38	5,5,0	1,3	3	2	6
8	7.40	0.45	2.28	5,0,0	1,2	6	3	5
9	4.50	3.45	12.39	5,5,10	3	5	2	3
10	10.36	6.24	4.26	10,5,5	1,3	7	1	2



5 CONCLUSIONS AND FUTURE WORK

In this work, a real-time dynamic data driven adaptive multi-scale simulation framework has been proposed for the economic and environmental load dispatching problem in power networks. The decision making capability of the framework resides in its algorithms developed for grid topology exploration and clustering, multi-objective optimization, state estimation, and fidelity selection. The framework also encompasses three databases for storing information related to sub-networks, fidelities, and measurements.

The proposed RT-DDDAMS framework has been demonstrated on a modified version of the IEEE-30 bus system. Presented results consistently reveal that the proposed framework is able to assess the system status and determine a simulation fidelity leading to a compromise solution which ranks among the global best possible solutions, while saving significantly from the computational resource utilization.

Future ventures of this research include both methodological and technological extensions to the proposed framework. Methodological extensions can be performed in the development of the fidelity selection and culling algorithm, combining the current selection procedure with an advanced optimal computing budget allocation (OCBA) algorithm to improve the quality of the solutions, while ensuring that a realistic computational threshold is respected. Furthermore, the effect of the variation in demand levels within the discovery procedure may be investigated to determine an optimal and feasible range. Technologically, the impact of integrating the RT-DDDAMS framework with high-speed sensor networks on the system's overall performance may be studied.

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AUTHOR BIOGRAPHIES

ARISTOTELIS EMMANOUIL THANOS is a Ph.D. candidate in the Department of Industrial Engineering at University of Miami (UM). His research interests include simulation and optimization of large-scale systems, with a focus on electrical systems. He can be reached at a.thanosfilis@umiami.edu.

XIAORAN SHI is a Ph.D. candidate in the Department of Industrial Engineering at UM. Her research interests include sequential Monte Carlo methods and integrated system simulations. She received UM Award for Graduate Research Activity in 2012. She can be reached at x.shi1@umiami.edu.

JUAN PABLO SÁENZ is a Ph.D. candidate in the Department of Industrial Engineering at UM. His research focuses on theory and application of multi-objective optimization methods. He can be reached at j.saenz4@umiami.edu.

NURCIN CELIK is an assistant professor at the Department of Industrial Engineering at the University of Miami. She received her M.S. and Ph.D. degrees in Systems and Industrial Engineering from the University of Arizona. Her research interests include architectural design and application of dynamic data-driven adaptive simulations for distributed systems. She has received several awards, including AFOSR Young Investigator Research Award (2013), UM Provost Award (2011), IAMOT Outstanding Research Project Award (2011). She can be reached at celik@miami.edu.