Procedia Computer Science
Volume 51, 2015, Pages 2543–2552
ICCS 2015 International Conference On Computational Science

A Dynamic Data-Driven Approach for Operation Planning of Microgrids

Xiaoran Shi, Haluk Damgacioglu, and Nurcin Celik*
University of Miami, Coral Gables, U.S.
celik@miami.edu

Abstract
Distributed generation resources (DGs) and their utilization in large-scale power systems are attracting more and more utilities as they are becoming more qualitatively reliable and economically viable. However, uncertainties in power generation from DGs and fluctuations in load demand must be considered when determining the optimal operation plan for a microgrid. In this context, a novel dynamic data-driven application systems (DDDAS) approach is proposed for determining the real-time operation plan of an electric microgrid while considering its conflicting objectives. In particular, the proposed approach is equipped with three modules: 1) a database including the real-time microgrid topology data (i.e., power demand, market price for electricity, etc.) and the data for environmental factors (i.e., solar radiation, wind speed, temperature, etc.); 2) a simulation, in which operation of the microgrid is simulated with embedded rule-based scale identification procedures; and 3) a multi-objective optimization module which finds the near-optimal operation plan in terms of minimum operating cost and minimum emission using a particle-filtering based algorithm. The complexity of the optimization depends on the scale of the problem identified from the simulation module. The results obtained from the optimization module are sent back to the microgrid system to enhance its operation. The experiments conducted in this study demonstrate the power of the proposed approach in real-time assessment and control of operation in microgrids.

Keywords: Microgrid operation, Dynamic data driven, Scale identification, Multi-objective optimization

1 Introduction

Distributed generation (DG), also known as on-site generation, refers to the production of electricity at or near the place of consumption using smaller-scale power generation resources and technologies. Based on this definition, a microgrid (MG) can be considered as a DG-based grid, which can operate in either *islanded* or *utility grid connected* modes. In the islanded mode, it is only the DGs that work to generate the power and satisfy the demand of the entire microgrid, whereas in the connected mode, the microgrid may utilize the electricity that is bought from the main grid as well as the one generated via its own DGs. Microgrids coordinate distributed generation resources in a more decentralized yet consistent way reducing the control burden on the grid and permit them to provide their full benefits

Selection and peer-review under responsibility of the Scientific Programme Committee of ICCS 2015

doi:10.1016/j.procs.2015.05.362

(Sfikas *et al.*, 2014). However, increasing penetration level of the distributed generation in a microgrid may increase security risks and cause faults in the energy system. Extreme conditions as well as issues with voltage violations, power losses, power quality, and reliability (Ackermann and Knyazkin, 2002) may occur unpredictably. Moreover, one of the main challenges of operating a microgrid is associated with the fluctuations of load demand and the power generated from the DGs, which may significantly rely on the weather conditions. These issues make the management of the microgrid in terms of the operation and planning difficult. From this point of view, a microgrid that can mitigate these fluctuations and operate in the most cost-effective manner is a necessary. To this end, in this study, a novel dynamic data-driven application systems (DDDAS) approach is proposed for determining the real-time operation plan for an electric microgrid. The proposed DDDAS approach 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, motivated by the DDDAS paradigm that was first presented by Darema (2000). Since its introduction, the DDDAS paradigm has been successfully applied to a variety of areas, such as supply chain system (Celik *et al.*, 2010), waste management (Parashar *et al.*, 2006), medical service (Gaynor *et al.*, 2005), amongst many others. Electric power distribution networks, more specifically the microgrids, are one of the challenging application areas to make use of the decidedly effective measurement and control processes available by utilizing DDDAS modeling techniques (Thanos *et al.*, 2014).

To this end, our proposed approach is equipped with a database, an agent-based simulation model embedding a rule-based scale identification procedure, and a multi-objective optimization module. In the database, data related to the MG topology (i.e., real-time load demand, electricity price from the utility market, etc.), as well as those obtained from the environmental sensors (i.e., solar radiation, wind speed, etc.) are stored. Upon the initialization of the simulation, the necessary first set of data is retrieved from the database, and more data is retrieved as the simulation progresses. In the simulation, the operation of the considered microgrid is simulated under various system uncertainties on an hourly basis. Meanwhile, a rule-based scale identification procedure is carried out, through which the complexity of the optimization problem is determined. Once the size of the problem is determined, the optimization module is executed to obtain the optimal operation plan for the microgrid in terms of the minimum operating cost and emissions. In order to solve the optimization problem, a novel particle filtering-based multi-objective optimization algorithm for operation planning of MG is proposed. The results of the optimization module are finally sent back to the MG system for execution. The performance of the proposed approach is demonstrated via a synthetic microgrid. The approach has been constructed in a generic manner so that it can be employed by any MG system that has similar types of DGs by importing the necessary data capturing its characteristics (i.e. number of DGs installed), topology, and environmental conditions into the database.

2 Proposed Approach

In this study, our goal is to determine the optimal hourly-based operation plan for a microgrid, whose load demand is satisfied with minimum operating cost and emissions. The components of our proposed approach are presented in detail in this section (see Figure 1 for overview).

2.1 Database

For easy adaptation of the proposed approach to varying types of microgrids with different characteristics, the heterogeneous data associated with the considered MG's topology, operations, and environment are stored in a database. The environmental data (i.e., wind speed, solar irradiance, temperature, etc.) is stored to estimate of the amount of electricity that can be generated from the renewable generation sources including the wind turbines and the solar panels. In the literature, several studies (i.e., Atwa *et al.*, 2010; Arefifar *et al.*, 2012) have used data that is generated using Weilbull probability density function (pdf) for wind speed and Beta pdf for solar data. In this study, rather than these synthetic functions, we incorporate a real-world sensory data for the wind speed, ambient temperature, and solar irradiance recorded at the Live Oak Station in Florida in 2010. These data are obtained from the Florida Automated Weather Network (FAWN) subsidiary of University of Florida (FAWN, 2013). The database also contains the microgrid topology data (i.e., load demand, market energy price, etc.) and the operational data for the distributed generators that characterize the load demand and operating cost of various DGs.

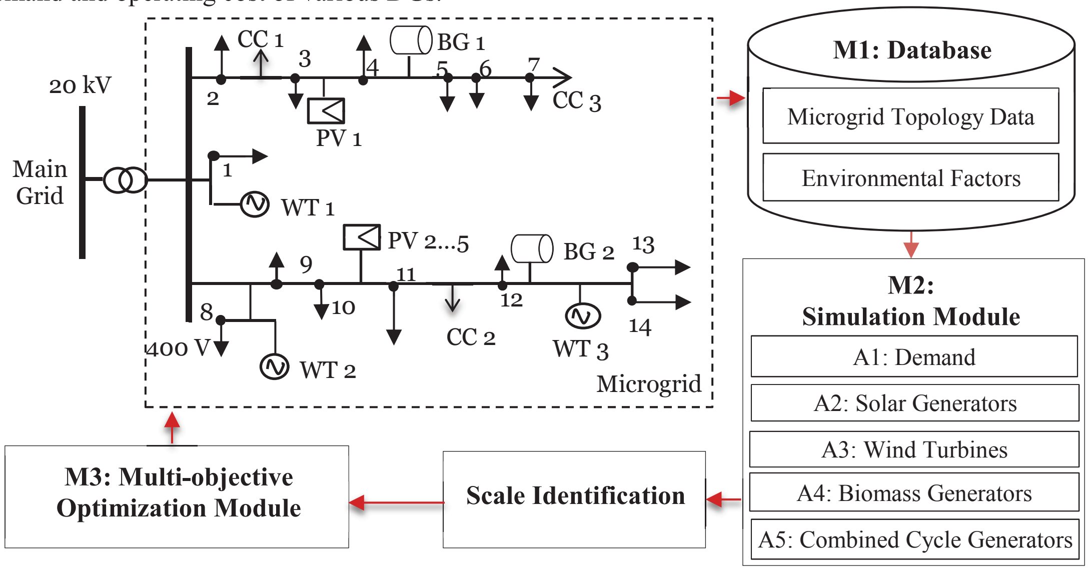


Figure 1: Proposed Dynamic Data-Driven Application Systems Approach Applied to a Considered Microgrid

2.2 Simulation Module and Rule-based Scale Identification Scheme

2.2.1. Agent-based Simulation Model for the Considered Microgrid

An agent-based simulation model provides an accurate representation of the considered microgrid while simultaneously capturing the behavior of operating components as well as their interactions with each other. In this study, the operating components including demand, solar panels, wind turbines, biomass generators, and combined cycle generators are designed as the agents.

- *Demand Agent*. Each building in the considered MG is defined as a demand agent. The data for the demand agent is obtained from the study conducted by Thanos *et al.* in 2014. Particularly, the data contains peak demand and hourly power factors of each building in the considered MG. Then, (1) is used to calculate the hourly demand D_h in the microgrid, where PD_i and PF_h represents the peak demand of building i and power factor at time h, respectively, and N is the number of buildings in the microgrid. The demand fluctuation for each building is modeled using the triangular distribution.

$$D_h = \sum_{i=1}^{N} PD_i \times PF_h \times triangular(0.95, 1, 1.05) \quad (1)$$

- *Wind Turbines Agent*. Wind turbines (WT) generate electricity using the wind power without producing any greenhouse gas emissions. The power generated by the WT is computed as shown in (2), where $P_{w,out}$ represents the total output power generated from the wind turbine, v_w is the real-time wind speed obtained from the wind sensors, v_{ci} and v_{co} denotes the cut-in and cut-out wind speeds, respectively, and v_{wr} is the rated wind speed. According to Sfikas *et al.* (2014) and Atwa *et al.* (2010), the wind turbine attributes shown in Table 1 are used in this study.

$$P_{w,out} = \begin{cases} 0, & if\ v_w < v_d \\ P_{wr} \times \frac{v_w - v_{ci}}{v_{wr} - v_{ci}}, & if\ v_{ci} \le v_w \le v_{wr} \\ P_{wr}, & if\ v_{wr} \le v_w < v_{co} \\ 0, & if\ v_w \ge v_{co} \end{cases} \quad (2)$$

Attributes of wind turbine	Unit	Value	Attributes of wind turbine	Unit	Value
Turbine capacity	kW	3000	Cut-out speed	(m/s)	25
Cut-in-speed	(m/s)	4	Rated speed	(m/s)	16

Table 1: Attributes of wind turbines

. *Solar Panels Agent*. Solar panels convert the solar irradiance into electricity. The power generated from the solar panels depends on the characteristics of the solar cell itself and on the weather conditions. Equations (3)-(6) are incorporated in the simulation to compute the power generated by the solar panels, where $P_{s,out}$ is the total output power generated from solar panels, FF is the fill factor related to the voltage at maximum power point V_{max}, the current at maximum power point I_{max}, the open circuit voltage V_{oc}, and the short circuit current I_{sc}. V denotes the voltage, which is a function of the open circuit voltage, the voltage temperature coefficient k_v and cell temperature calculated by the term $T_a + (T_n - 20)SI/0.8$. Here, T_a is the ambient temperature, T_n is the nominal operating temperature of the PV cell and *SI* is the solar irradiance. *I* shows the current, which is a function of the solar irradiance, the current temperature coefficient k_i, and the cell temperature. Attributes of the solar panels used in this study are given in Table 2.

$$P_{s,out} = FF \cdot V \cdot I \quad (3)$$

$$FF = \frac{V_{max} I_{max}}{V_{oc} I_{sc}} \quad (4)$$

$$V = V_{oc} - k_v \left[T_a + \frac{(T_n - 20)}{0.8} \cdot SI - 25 \right] \quad (5)$$

$$I = SI \cdot \left\{ I_{sc} + k_i \left[T_a + \frac{(T_n - 20)}{0.8} \cdot SI - 25 \right] \right\} \quad (6)$$

Attributes of PV cell	Unit	Value	Attributes of PV cell	Unit	Value
Open circuit voltage	V	21.98	Voltage temperature coefficient	mV/℃	14.4
Short circuit current	A	5.32	Current temperature coefficient	mA/℃	1.22
Maximum power voltage	V	17.32	Nominal cell operating temperature	℃	43
Maximum power current	A	4.76			

Table 2: Attributes of solar panels

- *Biomass Generators Agent*. Unlike the solar and wind, biomass is classified as base load controllable energy generation sources as it is not affected by environmental conditions. In this study, we use lower bound and upper bound in biomass modelling, as shown in (7), where $P_{bio,out}$ represents the amount of electricity produced from biomass generators. While lower bound (LB) satisfies to produce electricity smoothly, upper bound ensures that the energy generation does not excess the capacity of generator. In this study, the lower bound is assumed to be 20 percent of the biomass generator's capacity, and the upper bound is chosen as the 90 percent of the capacity.

$$LB \le P_{bio,out} \le UB \quad (7)$$

- *Combined Cycle (CC) Generators Agent*. Power generated from combined cycle generators is controllable on an hourly basis, as it presents desirable operational characteristics (i.e., wide range of operation hours, ease of operation setting up and shutting down, etc.). Moreover, they are not affected by external environmental conditions. To this end, in this study, the agent of combined cycle generators is modeled as a stand-by system that activates automatically when all other DGs fail to satisfy the total load demands. In this work, natural gas, fuel oil and propane are considered as fuels that are used in the combined cycle generators.

2.2.2. Scale Identification Scheme

In order to save computational resources and improve the efficiency in the decision making procedure, thereby to realize the real-time assessment and control of operation in a microgrid, a scale identification scheme is designed and incorporated in the simulation module for determining model fidelity within the optimization model, which then impacts the size of the considered optimization problem. Specifically, given the real-time MG load demand and DG generation capacities, the scales are determined based on rules shown in the following figure, where D_h represents the power demand in the microgrid at time h. Notations of the other parameters have been described in Section 2.2.1.

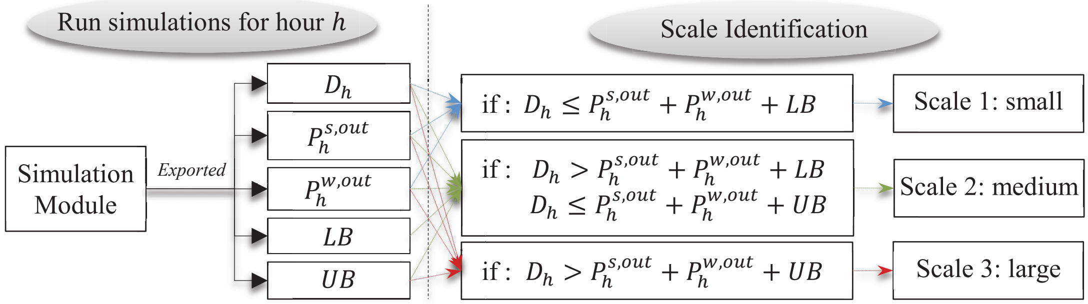


Figure 2: Scale Identification Scheme

For the small scale optimization problem (Scale 1), since the power generated from the solar panels, wind turbines, and biomass generators (with minimum generation capacity) can satisfy the demand in the entire microgrid, the combined cycle generators are not included in the optimization model. Moreover, there is no need to buy electricity from the main grid and the MG may sell the excess power to the market. For the medium scale optimization problem (Scale 2), two decision variables, which are the amount of electricity bought from the main grid and the amount of electricity generated from the biomass generators are added in the optimization model developed for Scale 1, so are the corresponding constraints. Scale 3 is the most complex one, under which the demand in the microgrid cannot be satisfied by the "green" distributed generation resources and the biomass generators. Therefore, the combined cycle generators, which are more expensive and less environmental friendly, have to be considered. As a result, decision variables that represent the amount of electricity generated from combined cycle generators at time h and corresponding constraints are added into the optimization model developed for Scale 2.

2.3 Particle Filtering-based Optimization

In this study, the optimization is executed based on the identified scales to determine the operation plan for the microgrid in terms of the minimum cost and emissions in any particular hour. These multi-scale problems are solved via a proposed particle filtering-based optimization algorithm.

2.3.1. Formulation of the Optimization Problem

Identification of the appropriate scales forms the basis for the optimization problems. Optimization is not required for Scale 1 since the demand can be 100% satisfied by the electricity generated from "green" DGs. Optimization is straightforward for the Scale 2 problem as well, in which only the minimization of the cost objective is considered. The formula to calculate the operating cost of the microgrid under Scale 1 is shown in (8), and the objective function and constraints for the optimization problem under Scale 2 are presented in (9)–(11). Here, v_b and f_b are the variable operating and maintenance (O&M) cost and the fuel cost of the biomass generators. Decision variables

$X_{b,h}$ and $X_{m,h}$ are the amount of electricity generated from biomass generators and amount of electricity bought from the main grid at hour h, respectively, and P_s and P_b are the market prices for selling and buying electricity.

$$C_{F1,h} = f_b * LB + v_b * LB \tag{8}$$

$$Min \quad C_{F2,h} = (f_b + v_b) * X_{b,h} + P_b * X_{m,h} \tag{9}$$

$$\text{s.t.} \quad P_h^{s,out} + P_h^{w,out} + X_{b,h} + X_{m,h} = D_h, \ \ \forall\, h \tag{10}$$

$$X_{b,h} \leq UB, \ \ \forall\, h \tag{11}$$

The optimization problem that needs to be solved under Scale 3 is more complex. Since the combined cycles are incorporated into the model, the problem becomes a bi-objective optimization problem. The two objectives, minimization of operating cost and emissions, and the corresponding constraints are provided in (12)–(16), where $X_{n,h}$, $X_{o,h}$, and $X_{p,h}$ are decision variables representing the amount of electricity generated by combined cycles with different types of fuels (i.e., natural gas, fuel oil, and propane), respectively; e_n, e_o, and e_p denote the carbon dioxide emission parameters of these generators; and Cap_n, Cap_o, and Cap_p are the corresponding capacities of these generators. In addition, v_c is the variable O&M cost of the combined cycle generators, and f_n, f_o and f_p are the fuel cost of natural gas, fuel oil and propane, respectively.

$$Min \quad C_{F3,h} = (f_b + v_b) * X_{b,h} + (v_c + f_n) * X_{n,h} + (v_c + f_o) * X_{o,h} + \left(v_c + f_p\right) * X_{p,h} + P_b * X_{m,h} \tag{12}$$

$$Min \quad E_{F3,h} = e_n * X_{n,h} + e_o * X_{o,h} + e_p * X_{p,h} \tag{13}$$

$$\text{s.t.} \quad P_h^{s,out} + P_h^{w,out} + X_{b,h} + X_{n,h} + X_{o,h} + X_{p,h} + X_{m,h} = D_h \ , \ \forall\, h \tag{14}$$

$$X_{b,h} \leq UB \ , \ \forall\, h \tag{15}$$

$$X_{n,h} \leq Cap_n; \quad X_{o,h} \leq Cap_o; \quad X_{p,h} \leq Cap_p \tag{16}$$

2.3.2. Implementation of the Optimization Algorithm

In this work, a particle filtering-based optimization algorithm is proposed to solve the aforementioned optimization problems. Particle filtering (PF) is a class of importance sampling and resampling methods applied for simulating the posterior probability distributions in Bayesian estimation problems (Shi and Celik, 2012). It is introduced by Gordon *et al.* (1993), and has gained popularity in recent years due to its advancements (i.e., flexibility, ease of implementation, capability of dealing with massive dataset, etc.) on a wide range of challenging applications.

The analogy of the proposed PF-based optimization algorithm to those of population-based optimization methods can be summarized as the following. First, the particles drawn from the distribution functions behave as if they are the candidate solutions generated from the solution space. Second, the importance weights assigned to these particles are then considered as the evaluation of the performances of the generated solutions. Last but not least, the sampling and resampling procedures in the PF algorithm are similar to the searching and updating procedures in the population-based optimization methods. To this end, we represent the optimization problem using a state-space model, in which the optimal solution is treated as a posterior state that is yet to be "estimated", and the optimal objective values observed are specified as an n-dimension measurements. The state-space model can be formulated mathematically as shown in (17)-(19), where $\vec{x}_k$ represents the state vector (decision variables), $\vec{y}_k$ is the minimum values of each objective for a minimization problem, $\vec{u}_k$ is the vector of processing noises, Y is objective vector, $\vec{x}^*$ is our target Pareto optimal solution, and k represents the iteration number.

$$\vec{x}_k = \vec{x}_{k-1} + \vec{u}_k, \quad k = 1,2, \ldots \tag{17}$$

$$\vec{y}_k = min \vec{f}\,(\vec{x}_k), \quad k = 0, 1, \ldots \tag{18}$$

$$\vec{x}^* = arg\, min_{\vec{x} \in X}\, \vec{Y} \quad or \quad \vec{x}^* = arg\, max_{\vec{x} \in X}\, \vec{Y} \tag{19}$$

The algorithm is mainly structured with an adaptive weighted allocation (AWA) procedure and a performance-based sampling and resampling procedure (PSR). The AWA procedure is developed for distributing the weights of multiple objectives gradually and periodically. In the PSR procedure, the optima is achieved an alternative is selected amongst all the possible solutions. The probability that the selected alternative is truly the "best", is controlled in each iteration. For ease of presentation, let us take a bi-objective minimization problem as an example here to explain the implementation of these two procedures. At the initialization step, N particles are randomly drawn within the solution space and equal importance weights $w_1^i = 1/N$ $(i = 1,2,\dots,N)$ are assigned to them. As the iteration progresses, particles are drawn from the transition prior (i.e., (17)), and the objective weights are generated via the AWA procedure, as provided in (20)-(21), where $|\cdot|$ provides the absolute value, A is equal to 0.99 and ε is 10^{-5}. These are parameters that are enforced to avoid extreme situations in which the importance factors of the objectives (O_1 and O_2) are equal to 1 or 0. The frequency of variation is controlled by the user-defined parameter Q, using which the AWA is able to approach the Pareto front dynamically as the number of iterations increases.

$$O_k^1 = A\left|sin\left(\frac{2\pi k}{Q}\right)\right| + \varepsilon \tag{20}$$

$$O_k^2 = 1 - O_1(k) \tag{21}$$

Given these particles, the corresponding objective values are calculated according to the objective functions, and two-dimensional measurements (i.e., $[y_{k1}, y_{k2}]$) are constructed via taking the minimum of each objective, as $y_{k1} = min(y_{k1}^1, y_{k1}^2, \dots, y_{k1}^N)$ and $y_{k2} = min(y_{k2}^1, y_{k2}^2, \dots, y_{k2}^N)$. Then, particles' importance weights with respect to each objective are calculated as $w_{k1}^i = g\left(y_{k1}\middle|x_k^i\right) * w_{(k-1)1}^i$ and $w_{k2}^i = g\left(y_{k2}\middle|x_k^i\right) * w_{(k-1)2}^i$ $(i = 1,2,\dots,N)$. The likelihoods $g\left(y_{k1}\middle|x_k^i\right)$ and $g\left(y_{k2}\middle|x_k^i\right)$ are presented in (22)-(23). Therefore, the importance weights of particles can be obtained via $w_k^i = O_k^1 w_{k1}^i + O_k^2 w_{k2}^i$. These particles are then ranked in an ascending order in terms of their importance weights. In the next iteration, the particles with small weights are discarded, and new particles are generated by adding a process noise to those particles with large importance weights (i.e., the transition prior). After several iterations, a mutation step will be triggered to break the local optima, in which an entire new set of particles will be randomly drawn. As the iterations progress, a set of promising solutions will be finally obtained. Figure 3 provides a visualized diagram of the PSR procedure.

$$g\left(y_{k1}\middle|x_k^i\right) = \varphi\left(f_1\left(x_k^i\right) - y_{k1}\right) = \varphi\left(f_1\left(x_{k-1}^i\right) - y_{k1}\right) \tag{22}$$

$$g\left(y_{k2}\middle|x_k^i\right) = \varphi\left(f_2\left(x_k^i\right) - y_{k2}\right) = \varphi\left(f_2\left(x_{k-1}^i\right) - y_{k2}\right) \tag{23}$$

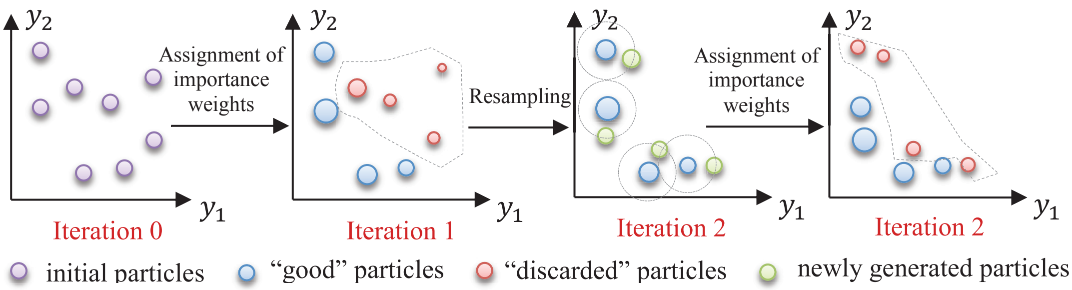


Figure 3: Performance-based Sampling and Resampling Procedure

3 Experiments and Results

In order to demonstrate the capabilities of the proposed approach, experiments are designed and carried out over a synthetic microgrid that is composed of 346 buildings (demand agents), 5 solar panels, 3 wind turbines, 2 biomass generators, and 3 combined cycle generators. Table 3 presents the operating costs for each type of DG resources. The variable O&M cost data are obtained from the report of NREL in 2010 (Tidball *et al.*, 2010). The fuel cost and carbon dioxide emission data is reported by Energy Information Administration (2013) and Green Econometrics (2007). The carbon dioxide emission of the fuel oil is provided by the Renewable Energy System (Quaschning, 2003). Moreover, we assume that the biomass resources are managed sustainably, therefore carbon dioxide emission of biomass generators is neutral (Environmental Protection Agency , 2014).

Explanation	Unit	Biomass	Wind	Solar	Natural gas	Fuel Oil	Propane
Variable O&M	$/MWh	6.71	-	-		2.00	
Fuel Cost	$/MWh	27.5	-	-	48	53	74
CO_2 emission	kg/KWh	-	-	-	0.1976	0.2802	0.2151

Table 3: Cost and carbon dioxide emission data

While the operation plan of the microgrid can be obtained for any time spanning the 365 days in a year, our analysis in this section focuses on two selected days, which are July 29th and December 26th in 2010. As weather conditions in winter differ greatly from those in summer and may significantly impact the power generated from the DGs, these two days are selected to present the differences on the obtained hourly-based operation plans and the scale identification in different seasons. In Figure 4, the daily operation plans that are obtained for the microgrid in the selected two days are presented. It is noticed that the biomass generators carried most of the burden to satisfy the power demand in the microgrid. Moreover, great differences have been observed on the number of occurrences of different scales identified in these two experimental days. During summer, due to the higher generation capabilities of the solar panels, load demand in the MG can be satisfied by the "green" distributed generators and the biomass generators most of time (23 out of 24 hours). However, during winter, operating the environment-friendly DGs alone cannot provide enough power for the microgrid. Differences on the operation plans for the MG in these two days reflect on the total cost and emissions as well. Specifically, in December 26th, the obtained best compromise solution is $22,241.5 in terms of cost and 1,313.6 Kg in terms of emissions, while in July 29th, they are $14,044.8 and 88.1 Kg, respectively, indicating that it is much economical and more environmental friendly to operate the microgrid in the summer.

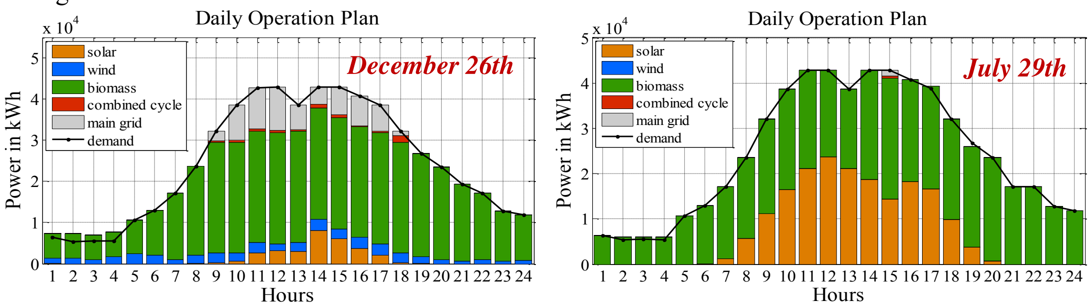


Figure 4: Daily Operation Plans for the Microgrid

In this study, additional experiments are carried out for demonstrating the performance of the proposed particle filtering-based multi-objective optimization algorithm with various number of iterations (i.e., $k = 50,100,200,500$). The Pareto-front obtained for these cases and the best cost and emissions obtained with different number of iterations are provided in Table 4, where the solutions are obtained from the operation plan for the microgrid at 11AM on December 26th. The resultant figures depicted that the proposed optimization algorithms have the capability to capture a great diversity of good solutions. It should also be noticed here that the algorithm's performance on producing a promising solution set is slightly impacted by the changing number of iterations. Therefore, it premises the potential to generate good results with reduced computational burden.

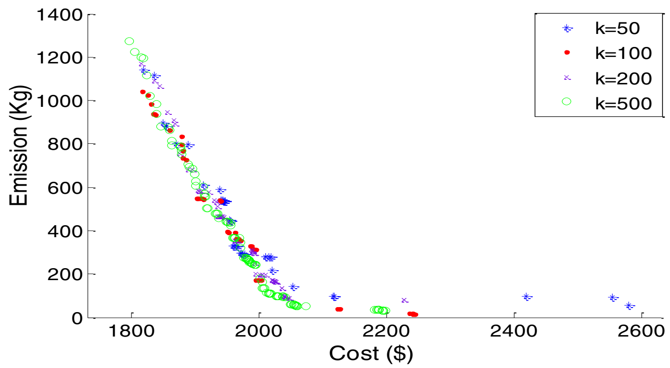
Non-Dominated Solution Set	Iteration	Best Cost	Best Emissions
	$k = 50$	\$1818.72	55.95 Kg
	$k = 100$	\$1816.45	15.96 Kg
	$k = 200$	\$1815.35	81.76 Kg
	$k = 500$	\$1787.34	24.20 Kg

Table 4: Comparison of Pareto-fronts and Extreme Solutions Obtained with Different Number of Iterations

4 Conclusion

In this work, a DDDAS approach is proposed for the operation planning problem within a microgrid. The proposed approach involves a database that stores the system-related operational, topological, and environmental data; an agent-based simulation simulating the operation of the microgrid considering the uncertainties of the power generated from the DGs and fluctuation of the demand; and an optimization module that solves the multi-objective optimization problem according to the scale identified by the simulation. The performance of the proposed approach is demonstrated via a synthetic microgrid with solar cells, wind turbines, biomass generators, and combined cycles. Results have shown that the proposed approach has the capability to provide real-time operation plan for the microgrid at any particular hour and have also indicated that the proposed particle filtering-based optimization algorithm can provide promising solutions without destroying the diversity of the solutions and occupying significant computational efforts. The proposed approach is developed in a generic manner. Therefore, it can be implemented for any microgrid that has similar types of distributed generators when sufficient changes are made to the database.

In the future, the storage devices and maintenance times of biomass generators in the microgrid will be taken into consideration when determining the operation plan. Moreover, since the performance of the particle filtering-based optimization algorithm may depend on several factors, such as the processing noises that control the efficiency of the sampling and resampling procedure; and the frequency of variation for importance factors of objectives (i.e., the parameter Q incorporated in (20)) that may affect the convergence of the algorithm together with the number of iterations, the optimal combination of these parameters will be investigated.

Acknowledgements

This project is supported by the AFOSR via 2013 Young Investigator Research Award (Award No: FA9550-13-1-0105).

References

Ackermann, T., and Knyazkin, V. (2002). Interaction between distributed generation and the distribution network: operation aspects. *Proceedings of IEEE/PES Transmission and Distribution Conference and Exhibition 2002*, (pp. 1357-1363). Yokohama, Japan.

Arefifar, S. A., Mohamed, Y. A., and El-Fouly, T. H. (2012). Supply-adequacy-based optimal construction of microgrids in smart distribution systems. *Smart Grid, IEEE Transactions on, 3(3)*, 1491-1502.

Atwa, Y. M., El-Saadany, E. F., Salama, M. M., and Seethapathy, R. (2010). Optimal renewable resources mix for distribution system energy loss minimization. *Power Systems, IEEE Transactions on, 25(1)*, 360-370.

Celik, N., Lee, S., Vasudevan, K., and Son, Y. (2010). DDDAS-based multi-fidelity simulation framework for supply chain systems. *IIE Transactions, 42*(5), 325-341.

Celik, N., Saenz, J., and Shi, X. (2012). Distributed generation penetration optimization based on particle filtering. *Proceedings of the 2012 Winter Simulation Conference*, (pp. 1-12). Berlin, Germany.

Darema, F. (2000). Dynamic data driven applications systems: A new paradigm for application simulations and a new paradigm for measurement systems. NSF Workshop, March 2000.

Energy Information Administration. (2013, February 14). *Carbon Dioxide Emissions Coefficients*. Retrieved from EIA: http://www.eia.gov/environment/emissions/co2_vol_mass.cfm

Environmental Protection Agency . (2014, May 22). *Clean Energy*. Retrieved from EPA: http://www.epa.gov/cleanenergy/energy-and-you/affect/air-emissions.html

FAWN. (2013, June 17). *FTP: Yearly CSV data.* Retrieved from Florida Automated Weather Network: ftp://agrofawn-prod01.osg.ufl.edu/fawnpub/data/hourly_summaries/

Gaynor, M., Seltzer, M., Moulton, S., and Freedman, J. (2005). A dynamic, data-driven, decision support system for emergency medical services. *Proceedings of the International Conference on Computational Science (ICCS)* (pp. 703-711). Berlin: Springer-Verlag.

Gordon, N., Salmond, D., and Smith, A. (1993). Novel approach to nonlinear/non-Gaussian Bayesian state estimation. *IEEE-Proceedings-F, 140*, 107-113.

Green Econometrics. (2007, August 27). *How to measure fuel efficiency, energy costs, and carbon emissions for home heating*. Retrieved from Green Econometrics: http://greenecon.net/how-to-measure-fuel-efficiency-energy-costs-and-carbon-emissions-for-home-heating/energy_economics.html

Parashar, M., Matossian, V., Kile, H., Thomas, S., Wheeler, M., Kurc, T., *et al.* (2006). Towards dynamic data driven management of the ruby golch waste repository. *Proceedings of the International Conference on Computational Science (ICCS). 3993*, pp. 384-392. Berlin: Springer-Verlag.

Quaschning, V. (2003). *Specific Carbon Dioxide Emissions of Various Fuels*. Retrieved December 10, 2014, from Regenerative Energiesysteme (Renewable Energy Systems): http://www.volker-quaschning.de/datserv/CO2-spez/index_e.php

Sfikas, E., Katsigiannis, Y., and Georgilakis, P. (2014). Simultaneous capacity optimization of distributed generation and storage in medium voltage microgrids. *Electrical Power and Energy Systems*, 101-113.

Shi, X., and Celik, N. (2012). A minimum relative entropy-based density selection scheme for Bayesian estimations of energy-related problems. *Proceedings of the Annual Industrial and Systems Engineering Research Conference*, (pp. 769-778). Orlando, FL, USA.

Thanos, A., Moore, D., Shi, X., and Celik, N. (2014). System of systems modeling and simulation for microgrids using DDDAMS. In A. Tolk, & L. Rainey, *Modeling and Simulation Support for Systems of Systems Engineering Applications.* Hoboken, NJ, USA: Wiley and Sons Inc.

Tidball, R., Bluestein, J., Rodriguez, N., and Knoke, S. (2010, November). *Cost and Performance Assumtions for Modelling Electricity Generation Technologies.* Retrieved from National Renewable Energy Laboratory (NREL): 1–211. Sub-contract Report, NREL/SR-6A20-48595: http://www.nrel.gov/docs/fy11osti/48595.pdf