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EFFICIENT DESIGN SELECTION IN MICROGRID SIMULATIONS

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ABSTRACT

Microgrids (MGs) offer new technologies for semiautonomous grouping of alternative energy loads fed into a power grid in a coordinated manner. Simulations of these microgrids are time critical yet computationally demanding, inherently complex, and dynamic, especially when they are constructed for control purposes. In this paper, we address the design ranking and selection problem in MG simulations from a set of finite alternatives in the presence of stochastic constraints. Each design encapsulates a different level of control of the segregation mechanism within the system, and a performance function measured as a combination of the incurred cost and energy surety. Building on this performance function, optimal computing budget allocation (OCBA) method is used to efficiently allocate simulation replications for selecting the best design with significant accuracy and reasonable computational burden. Computational results on a multi-scale MG testbed have shown that OCBA algorithm outperforms equal and proportional to variance allocation of replications.

1 INTRODUCTION

Microgrids (MGs) are self-balancing networks that have the ability to integrate a diversity of generation assets and fuel sources (i.e., internal combustion engines, gas turbines, microturbines, photovoltaic arrays, fuel cells, and wind turbines) to the distributed power grid and its operations. Being smaller counterparts of the main electricity grid, MGs offer a prodigious potential for enhanced economic load dispatch. The control for MGs meanwhile can be sustained or revised based on varying rate structures and generation costs. In addition, MGs have the capability to isolate from the main network and operate independently in case of a detected network abnormality or even emergency. Because of these advantages, MGs present a great potential to maintain a network's energy surety even in crisis situations within operation-safe boundaries by relying only on its own resources (NREL 2012, Pogaku et al. 2007). Microgrid systems may further control their demand by isolating areas and satisfying only some specific portions of the total demand based on their energy surety priorities (i.e., critical demand) (Thanos et al. 2013).

On the other hand, control in an MG entails several unique challenges. Unlike conventional power grids, an MG may host a mix of both traditional and new generation sources (Sáenz et al. 2012). Hence, advanced control mechanisms are needed to ensure an MG's self-regulation of voltage and frequency in a robust manner (Celik et al. 2013). Detailed response characteristics of engines and regulators should also be studied, as the traditional power-flow assessment is inadequate and commonly exclude renewable technologies (Sáenz et al. 2013). In order to facilitate stability and power quality in MG operations, particularly during network disturbances, sophisticated optimization methods are also required.

To this end, optimization techniques, which are embedded into simulation practice, may present a solution mechanism for the considered multi-objective problem of control in MGs. Through simulation based optimization, the entirety of these complex systems can be realistically modeled to provide useful operational and managerial decision supports (Fu 2002). Simulation optimization modeling can be applied to many complicated MG-related real-world systems including automated response systems, electrical systems with multiple loads and distributed energy resources, and electricity reliability systems. The performance, however, of these models come at the expense of substantial computational power. This is especially true when dealing with large number of alternative designs, making simulation efficiency a significant issue to handle.

Several different approaches have been investigated in the literature to rank and select alternative designs in simulation. Goldsman and Nelson (1994) first argued that the statistical methods of ranking, and selection, and multiple comparisons are applicable to cases where there exist comparisons among a finite number of systems. In the same study, Goldman and Nelson (1994) proposed ranking methods for four classes of problems namely, screening a large number of system designs, selecting the best system, comparing all systems to standard, and comparing alternatives to a default; all of these are majorly related to statistical multiple-comparison procedures. Even so, Goldsman and Nelson (1994)'s approach was not applicable to intricate problems such as circuit-based elements, discrete electrical resources with multiple loads, or smart grids with large number of designs. Later, Chen et al. (1997) introduced the Optimal Computing Budget Allocation (OCBA) technique to efficiently select the best designs over k alternatives. The comparison of results of traditional two-stage procedures with their proposed method revealed that OCBA proved to be more than ten times faster (Chen et al. 1997). In order to further improve the OCBA method, Chen et al. (2000) proposed a new and improved way to allocate simulation designs, which helps minimize the simulation time. Their approach was essentially developed to select the best design among a finite number of designs by maximizing the probability of correct selection ($\mathrm{p}\{\mathrm{CS}\}$) of different design replications. Experiments were conducted by selecting the design with the smallest (or largest) expected value of simulation output for the minimization (or maximization) problem among k alternative designs with unequal or even unknown variances. Results showed that the improved OCBA was able to reach a desirable confidence level faster than theoretically optimal allocation (TOA) (Chen et al. 2006), equal allocation, and proportional to variance (PTV) allocation. OCBA was later applied to semiconductor scheduling problems (Hsieh et al. 2007) and extended to more general problems (Yan et al. 2012, Chen et al. 2013). Meanwhile, inspired by the fact that most real-life problems are multi-objective, Lee et al. (2004) provided a selection method for the multi-objective ranking and selection problem (MOCBA). Due to the nature of their multi-objective problem, the results were shown as a Pareto optimality set rather than a single datapoint (i.e., the best one). When using this improved method, MOCBA reached the desirable confidence level 50-100% faster than theoretical optimal allocation (TOA) and uniform allocation (UCBA). On the other hand, the application of MOCBA to the complex and dynamic simulations of MGs that are especially constructed for multi-objective control purposes would not be as promising as what has been shown in the synthetic experiments of Lee et al. (2004). It has been concluded that this discrepancy is caused by the fact that the results for the considered MG are possibly having an area of undesirable non-dominated solutions. Here, MOCBA would allocate some additional replications (out of the scarce and much needed ones) to simulation designs whose non-dominated solutions enclose very low cost and energy surety simultaneously. Such solutions, which result in low operational costs associated with low energy sureties, are unacceptable for most microgrid operations.

In this paper, being motivated to take on this experiment by the growing urgency in the advancement of MG modeling and control as well as by the unique challenges MGs provide, we study the design ranking and selection problem in MG simulations from a finite set of alternatives of their control mechanism in the presence of stochastic constraints for the allocation of simulation replications. To this end, we formulate the simulation performance as a single objective function that combines both cost and energy surety (demand satisfaction percentages). Utilizing this performance function, we then assign simulation replications to design alternatives in an effective manner using OCBA.

The rest of the paper is organized as follows: In Section 2, we provide the details of the proposed design selection approach in microgrid simulations along with a brief background of the studied OCBA algorithm. In Section 3, we provide the topological details of the considered microgrid system. We then discuss the modeling details our multi-scale migrogrid testbed in the same section. In Section 4, we present the results obtained from experiments that were conducted in our multi-scale microgrid testbed with different numbers of alternative scenarios and compare the performance of OCBA to that of equal replication allocation and proportional to variance (PTV) allocation of replications. Finally, in Section 5, we summarize the conclusions of findings and discuss the future venues of this work.

2 PROPOSED DESIGN SELECTION IN MICROGRID SIMULATIONS

Microgrids, by their networking structure, may include various distributed energy demands and resources which collectively make their simulation computationally demanding. This is especially true when these simulations are designed for operational and control purposes. Furthermore, when these simulations are built and run in higher fidelities (or in greater details), data injections, dispatch updates, and crisis-related system responses occur in higher frequencies. This makes it even more complex and, therefore, difficult to obtain the best decisions under uncertain circumstances. However, simulating a microgrid system with a high fidelity model (hence using up significant computational resources) may not necessarily lead to a better allocation of energy distribution to its customers; this fact is unacceptable in situations where the response time is critical. Hence, the goal in simulating those systems is to run those simulations in the highest fidelity (or design) only when it is needed.

In this work, the diversity of demands in microgrid networks is elucidated via three categories of electrical loads, namely: critical, priority, and non-critical. The nodes with critical demand (i.e., demand for healthcare and military facilities) have the highest priority amongst all, as any instance in its supply may have a direct impact on national security. The nodes with priority demand have a lower level of urgency than those of critical nodes and mostly correspond with industrial loads. Finally, the nodes with non-critical demands include housing and shopping facilities. Based on the defined categories of electrical loads, five unique fidelities of simulations (i.e., designs) are investigated in this study. These fidelities represent the various levels of control of the microgrid over the demand (i.e., the number of isolation points strategically placed within the microgrid). For instance, in a Fidelity 5 design, the model has the highest degree of detail and control over the considered system in terms of isolation points as each building may be disconnected from the networked grid singlehandedly if a particular abnormality occurs in its nearby environment. Conversely, in a Fidelity 1 design, the model has the lowest degree of detail and control over the considered system with only one main isolation point. In this fidelity, the model may decide to connect and disconnect the entire microgrid from the main network, yet does not have the capability to single out the demand of each building or feeder. Overall, as the fidelity heightens, so does the expected computational intensity and accuracy of the model. Hence, the decision of selecting the right fidelity is a critical one due to the scale, complexity, and significance of the considered models. In this work, we address the fidelity (or design) ranking and selection problem in MG simulation models from a finite set of alternatives in the presence of multiple objectives for the allocation of simulation replications.

In order to achieve a desirable accuracy level in our results, while effectively assigning the scarce resources for simulation replications, we exploit the OCBA algorithm that captures the randomness and physical state of the system while also optimizing the computing budget allocation. In the next subsections, we present the mathematical formulation of our problem followed by the details of the solution approach provided by OCBA.

2.1 Formulation of Ranking and Selection Problem in MG Simulations

In this section, we present the formulation of ranking and selection problem in MG simulation models along with the model fidelities and their components that are considered in this work. In our MG simulation models, there are k alternative designs consisting of the combinations of fidelity control levels assigned for each different microgrid. In our considered case study, the number of different fidelities for each MG is limited to 5. Our case study also investigates three networking structures containing one (1-MG), two (2-MG), and three (3-MG) independent microgrids respectively, each with five different levels of fidelities. Thus, we have 5, 25, and 125 different combinations of model fidelities for these 1-MG, 2-MG, and 3-MG structures, respectively. These different combinations are illustrated as a set of two different paths in Figure 1. For example, in the testbed containing 3-MGs, the red lines represent the design when fidelities are set to level 2 for the first microgrid, to level 3 for the second one, and to level 5 for the third one. The set of alternative designs that we use in this work contains all combinations shown in Figure 1 and is envisioned to shed light on the performance of the studied model when applied to problems at varying selection complexities.

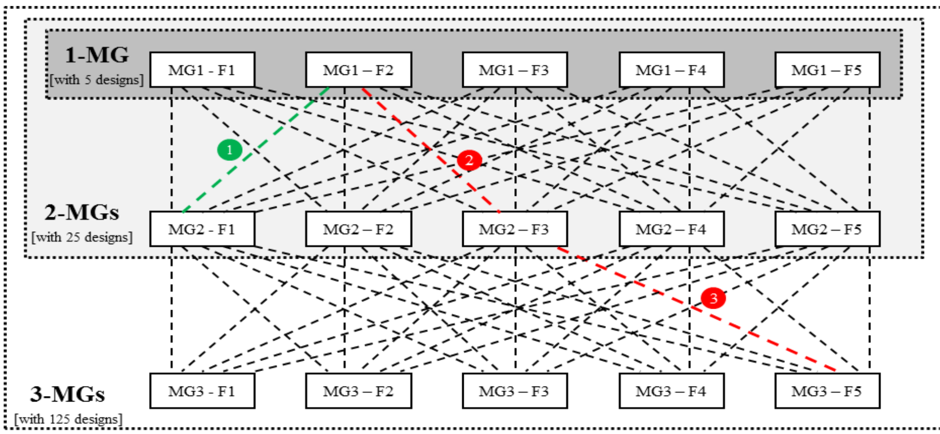

Figure 1: Considered control designs for various networking structures.

In terms of the notation in formulating the problem of finding the best simulation design among k designs (k =5, 25,125 for 1-MG, 2-MG, and 3-MG, respectively) that maximizes the MG's performance, n_i is the number of simulation replication for design i, N is the total number of available simulation replications (i.e., budget), f_{ij} is the MG performance of the j^{th} replication of design i, $\bar{f_i}$ is the expected performance of design i where $\bar{f_i} = \sum_{j=1}^{n_i} f_{ij}/n_i$, $S_{f_i}^2$ is the sample variance of the MG performance for design i where $S_{f_i}^2 = \sum_{j=1}^{n_i}(f_{ij} - \bar{f_i})^2/(n_i - 1)$, b is the design with the largest sample MG mean performance, and μ_{f_i} is the mean of MG performance for design i (unknown).

After performing n_i initial simulation replications for each design i, we search for the highest expected MG performance among k designs, which is denoted as b. However, the expected performance of design i ($\bar{f_i}$) has variability indicating that b does not necessarily lead to the largest unknown MG mean performance for design i (μ_{f_i}). To this end, Chen and Lee (2010) define the probability of correct selection $P\{CS\}$ which represents the probability of i_{best} to be the best selection. This probability of correct selection is formulated in Equation (1).

$$P\{CS\} = P\{design\ b\ is\ actually\ the\ best\ design\} = P\{\mu_{f_b} > \mu_{f_i}, i \neq i_{best} | i = 1,2, \ldots, k\} \quad (1)$$

Since the goal in the OCBA method is to maximize the probability of correct selection while the total computational budget is fixed to N replications, the model can be written as follows (Chen et al. 1998):

$$\begin{aligned} & max_{n_1,\ldots,n_k}\, P\{CS\} \\ s.t. \quad & n_1 + n_2 + \ldots + n_k \leq N \end{aligned} \quad (2)$$

Acquiring the solution for Equation (2) is not a trivial task since, there is no closed-form expression for the confidence level of $P\{CS\}$. Furthermore, since the mean and variance of the MG performance are both unknown, there is a need to simulate all the different alternative designs to compute $P\{CS\}$ for the MG performance function. Consequently, the total number of replications for $n_1, n_2, \ldots, n_k$ is large for even moderate k. Addressing these challenges, Chen et al. (2009) develops an effective approach adopting a Bayesian model to solve the budget allocation problem, where the outcomes are shown to outperform the classical models of $P\{CS\}$ estimation such as equal allocation and theoretically optimal allocation (TOA). Because when simulating our MG system both mean (μ_{f_i}) and variance ($\sigma_{f_i}^2$) are unknown, the prior distribution for the output (f_{ij}) is assumed to have a gamma-normal distribution in the Bayesian model. Assuming that the MG performance is unknown prior to running experiments, the posterior distribution of μ_{f_i} can be assumed to follow a t-distribution with mean $\overline{f_i}$, precision $n_i/S_{f_i}^2$ and $n_i - 1$ degrees of freedom. As an alternative to the traditional yet time-consuming method of estimating $p\{CS\}$ via Monte Carlo simulations, Chen (1996) proposes a fast and inexpensive method, namely Approximate Probability of Correct Selection (APCS), to estimate the lower bound of $p\{CS\}$ within the budget allocation procedure. The advantage of APCS methods is the simplicity of computation where the computational burden is lightened with the calculations of a product of pairwise comparison probabilities (i.e., P($\mu_{f_b} > \mu_{f_i} | for\ f_i \neq f_b$)). Similarly, we can calculate the approximate probability of correct selection ($P\{CS\}$) with Bonferroni inequality as shown in Equation (3) (Chen and Lee 2010):

$$APCS - B \equiv 1 - \sum_{i=1, i\neq b}^{k} P\{\mu_{f_b} < \mu_{f_i}\} \tag{3}$$

The approximate $P\{CS\}$ can be calculated using product form or the Bonferroni inequality (Equation (3)), both of which converge at $P\{CS\}$.

In this paper, in order to speed up the proposed OCBA algorithm in MGs, the maximum of both (i.e., max($APCS - P$, $APCS - B$) is exploited for the confidence level. Using the procedure for maximizing P{CS} by Chen and Lee (2010), we have applied the OCBA algorithm to our problem of effectively selecting the best MG simulation design from a set of alternatives. Details of our modified OCBA algorithm are presented in the following subsection.

2.2 Ranking and Selection in MG Simulations using OCBA

Considering the aforementioned design ranking method in Section 2.1, a sequential approach based on the OCBA algorithm for selecting the best MG control designs is presented in this section. As the simulation proceeds through our algorithm, we compute the mean and variance of MG's performance from the data which is collected up to that stage. The algorithm is presented as follows:

Step 1. Parameters k (number of alternative designs), N (total simulation budget), Δ (available budget for one iteration of the algorithm), and n_0 (initial replications for each design) must be entered as inputs. In this algorithm, l depicts the current iteration in OCBA. Depending on the input parameters, n_0 replications have to be performed for each design during initialization.

$$l \leftarrow 0;$$
$$n_1^l = n_2^l = \cdots = n_k^l = n_0$$

While $\left(\sum_{i=1}^{k} n_i^l < N\right)$ repeat steps 2-4:

Step 2. Calculate the expected value of MG performance for each design $\overline{f_i} = \frac{1}{n_i^l}\sum_{j=1}^{n_i^l} f_{ij}$ and the corresponding standard deviations $s_{f_i} = \sqrt{\sum_{j=1}^{n_i^l}(f_{ij} - \overline{f_i})^2 / n_i^l - 1}$, $i = 1,2, \ldots, k$.

Step 3. Calculate the new replications for MG designs (n_1^{l+1}, n_2^{l+1}, … , n_k^{l+1}) using the following equations where b is the design with the best performance:

(1) $\frac{n_i^{l+1}}{n_j^{l+1}} = \left(s_{f_i}\,(\bar{f}_b - \bar{f}_j)/s_{f_j}\,(\bar{f}_b - \bar{f}_i)\right)^2 \;, for\ i > j,\ i,j \neq b$

(2) $n_b^{l+1} = s_{f_b}\sqrt{\sum_{i=1,i\neq b}^{k}\left(n_i^{l+1}/s_{f_i}\right)^2}$

Step 4. Perform additional $\left[\max\left(n_i^{l+1} - n_i^{l}, 0\right)\right]$ replications (for design i); $l \leftarrow l + 1$.

In the proposed algorithm, the best design b may change in each iteration l. However, by increasing the number of iterations, in most cases the best design converges to the optimal design as l goes to infinity (the probability of correct selection approaches very close to 1). It should be noted here that the initial number of simulation (n_0), and one-time increment (Δ) should not be selected to be too small in order to avoid a poor estimation of the mean and variance. Moreover, the more expensive the simulation is, the smaller Δ should be selected to achieve better accuracy.

2.3 Definition of the proposed MG Performance Function

In order to utilize the OCBA method, the performance of the simulation for each alternative design has to be evaluated. In our case, to simulate a microgrid system under different control designs, we consider two objectives, namely: 1) minimizing the total cost of operations and 2) maximizing the percentage of the energy surety. However, within the considered system simulation, satisfying the highest amount of critical demands, is more crucial than minimizing the total cost. Hence, obtaining a Pareto frontier for the considered multi-objective problem becomes a focal issue. Figure 2 indicates a sample solution set for the aforementioned two-objective optimization problem. The red and blue points represent the non-dominated and dominated solutions, respectively. It can be noticed that all the solutions in the lower part of the Pareto frontier (lighter red points) appear to have a very low cost but, at the same time, very low energy surety. Hence, plenty of the non-dominated solutions in the Pareto frontier would be unrealistic for the considered MG system. For instance, a zero cost can be achieved at all times by disconnecting all of the buildings from the grid. This is, of course, unacceptable since the demand would never be satisfied.

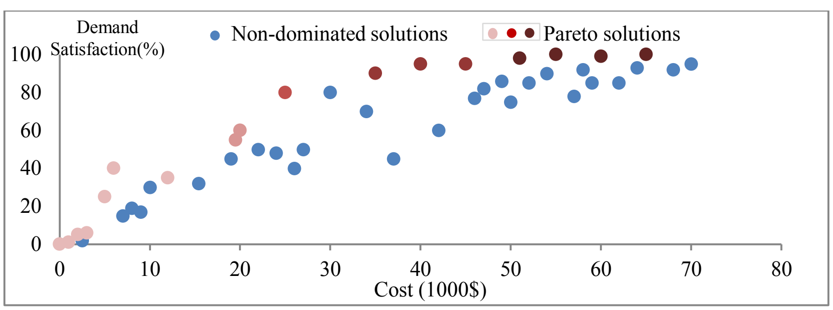

Figure 2: Solution set for multi-objective optimization problem.

As the simulations developed in this study, in order to address the multi-objective control problem within MGs, face a significant restriction in terms of their replication length as well as times, any unnecessary replications of unviable designs should be eliminated. As the MOCBA method discussed in Section 1 would run a number of simulations for designs in the Pareto frontier that could be easily disregarded in our application, it is not adopted in this work. Alternatively, a MG performance function that combines the total operational cost of the MG and average percentage of satisfaction for different load types during the simulation time is proposed as shown in Equation (4).

$$f(X) = a \cdot P_{crit} + b \cdot P_{pr} + c \cdot P_{ncrit} + d \cdot \frac{C_{max} - C}{C_{max}} \tag{4}$$

where X is the design for which the performance is evaluated, P_{crit}, P_{pr}, and P_{ncrit} are the percentages of energy surety of the critical, priority and non-critical loads respectively, C_{max} is the maximum cost calculated so far between all replications and designs, C is the cost of the current replication for design X and a, b, c, and d are the coefficients of the percentages of energy surety and cost and correspond with the priority that is given to the different objectives.

The numeric outputs obtained for the operational cost of MGs and percentages of the energy surety are in different scales (i.e., energy surety percentage ranges from 0 to 1 while the operational cost of MG can be any positive number from zero to millions of dollars, depending on the considered system). Because of this, the solution space of the proposed performance function needs to be well-adjusted. Furthermore, the proposed performance evaluation function is expected to return higher values as the cost decreases with a fixed energy surety percentage. In order to address these challenges, the percentage of the marginal decrease of the cost of the current design is compared to that of the worst possible cost realized so far in the simulation. As the considered economic load dispatch (ELD) problem is solved in our microgrid simulation, the maximum cost is not expected to be highly unmanageable, since the solution set is restricted into a feasible region. The coefficients for the considered multiple objectives correspond to their priority determined by subject matter experts. In our experiments, $a, b, c,$ and d, are set to 20, 8, 2, and 1, respectively making the total energy surety percentage 30 times more important than cost reduction percentage, and the critical energy surety 2.5 times more important than priority energy surety as well as 10 times more important than the non-critical energy surety.

3 MULTI-SCALE MICROGRID TESTBED

In this work, in order to validate our proposed algorithm for selecting the control design that leads to the best performance in terms of cost and energy surety, we designed a simulation model in which, given the specific control scheme for the MGs, the Economic Load Dispatch (ELD) problem must be solved. ELD problem searches for the best possible power resource management so that the total operational cost of a power network is minimized, while ensuring that the total demand is satisfied, and the generators' capacities are not exceeded. The ELD problem is formulated below in Equations (5), (6) and (7). The last two equations represent the constraints for the power balance and the generators' capacities, respectively.

$$\min \quad z = \sum_{i=1}^{N} \left(a_i + b_i G_i + c_i G_i^2\right) \tag{5}$$
$$s.t. \quad \sum_{i=1}^{N} G_i + \sum_{j=1}^{M} R_j = D_{tot} + P_{loss} \tag{6}$$
$$G_i^{min} \le G_i \le G_i^{max} \qquad \forall i \tag{7}$$

where a_i, b_i, and c_i are the cost coefficients for the i-th diesel generator, G_i is the generation of the i-th diesel generator, R_j is the generation of the i-th renewable source, N is the total number of diesel generators, M is the total number of renewable sources, D_{tot} is the total demand in the network, P_{loss} is the power loss, and finally G_i^{min} and G_i^{max} are respectively the minimum and maximum power generation of the i-th generator.

In case of a microgrid with a capability to connect, disconnect, and reconnect to the main power grid via multiple nodes, the aforementioned ELD optimization problem has to be solved in a nested form, so that when the microgrid is in islanding mode and there is not sufficient energy for satisfying the total demand, the optimization problem incorporates a second objective to maximize the energy surety, while the cost is minimized. By solving the ELD problem within each simulation replication, our simulation model ensures that the performance of the MG system is optimized under the specified predetermined control design. In this way, the OCBA algorithm uses as a performance measure for each simulation design the optimal cost and optimal demand satisfaction under the current control scheme.

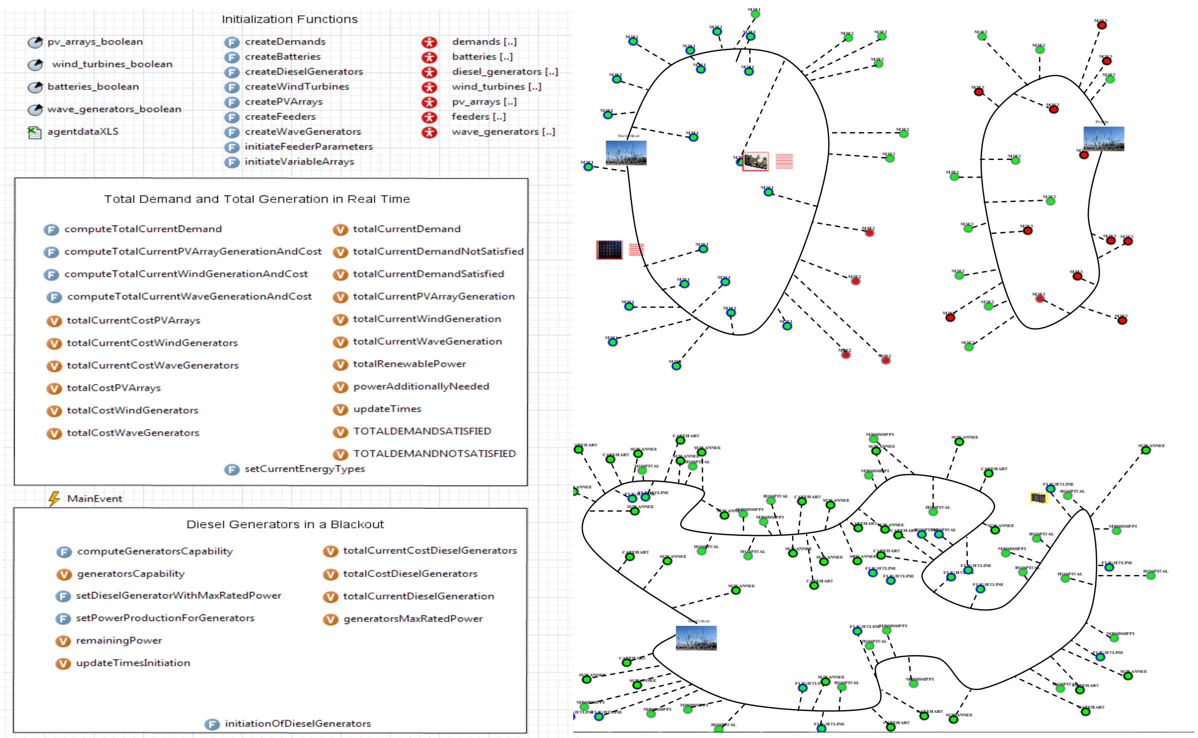

Figure 3: Overview of the MG simulation.

In our simulation model, operations and interactions among the different autonomous systems of the same electrical environment of MGs are captured via agent-based modeling in a multi-scale testbed. Our agent-based simulation model of MGs include 7 separate classes of agents representing the demand, solar energy, wind energy, wave energy, batteries, diesel generators, and feeders. In our multi-scale testbed, the total number of agents ranges from 200 to 334. Each agent, meanwhile, contains several variables and functions for the simulation of its operation. Additionally, the agents for the renewable energy generation are fed with data from weather databases in an effort to create more accurate and realistic computation of the energy generated, according to their capabilities. All of the agents are connected to each other and communicate in an environment that coordinates their control by optimizing their operations. This environment is also responsible for generating some of the uncertainties of the system, such as the creation of random blackouts and faults. In Figure 3, a partial screenshot of the simulation model is shown. On the left, some of the system variables and functions are listed, while on the right, the topology of an active MG with 3 feeders in a specific moment is depicted. Here, the green nodes represent the buildings in the MG for which the demand is satisfied, while the red nodes represent the buildings that are disconnected from the grid. The aforementioned brief description of the simulation model reveals that the problem of simulating an MG may be highly complicated and computationally intractable. Therefore, optimizing the number of simulation replications is extremely crucial for achieving the selection of a near optimal design with high probability within an acceptable time frame.

4 RESULTS

In this section, we provide the details of our experiments in MG selection and present the results obtained from our proposed design selection approach in comparison with the results obtained from Equal Allocation

(EA) and Proportional to Variance (PTV) algorithms that exist in the literature. For consistency purposes, the very same settings of sequential sampling that is used for the OCBA algorithm is also used for EA and PTV algorithms. In our experiments, the coefficients of the objective function $a, b, c,$ and d, are set to 20, 8, 2, and 1 respectively, as mentioned in section 2.3. For the comparison of the three algorithms, we use the total number of replications needed to reach the desired probability of correct selection instead of measuring the total computational time. This is because the magnitude of the computational time needed to run the algorithms is insignificant when compared to the computational time needed to run the simulation replications. It is noted here that speeding up the simulation-optimization procedure is only desirable when the simulated system is complex and time consuming, as in our case.

In our experiment scenarios, we initially ran n_0 simulation replications for each design, and as the procedure advanced, the computed probability of correct selection (P{CS}) was updated at each step. This procedure repeats itself until a desirable P{CS} is met. In the following, we briefly explain the EA and PTV algorithms that are used for benchmarking in this work.

4.1 Overview of Equal Allocation and Proportional to Variance Algorithms

Equal allocation is the simplest and most common method for simulation allocation, in which the simulation budget (i.e., replications) is equally allocated among all possible designs (i.e., fidelities). Accordingly, $n_i = N/K$ is the simulation budget allocated for each MG simulation design or fidelity considered in this research. One-time computing budget allocation (Δ) and initial number of simulation (n_0) are kept the same during the experiments for both the EA and OCBA algorithms.

A modified version of the PTV algorithm is exploited in this study as an additional source for comparison purposes. This method is mainly dependent on estimated variance of initial replications for each design (n_0). Initially, all k designs are simulated for n_0 replication where n_0 is pre-determined. Then, the number of additional simulations required in the second stage is determined by using the sample variance ($s_{f_i}^2$) estimated from first stage as in (8).

$$N_i = \max\left(0, \lceil s_{f_i}^2 h^2/d^2 \rceil - n_0\right), \quad i = 1,2,\ldots,k, \tag{8}$$

where d is the indifference zone (significant magnitude of the variance) and h is a constant that solves Rinott's integral. For the setting of this work we use a sequential modified version of the PTV algorithm that excludes the indifference-zone parameter. Hence, the following equation is utilized to compute the new budget allocation:

$$n_1^{l+1}/s_{f_1 1}^2 = n_2^{l+1}/s_{f_2}^2 = \cdots = n_K^{l+1}/s_{f_k}^2 \tag{9}$$

4.2 Ranking and Selection of MG Simulations

In this paper, we consider three different networking structures involving one, two, and three independent microgrids, respectively (i.e., 1-MG, 2-MG and 3-MG), where our goal is to find the best design with appropriate confidence level (P{CS}) to maximize the overall MG performance function. To this end, OCBA, PTV and EA algorithms are applied to find the best design with minimum computational time. During the implementation of the OCBA algorithm, the initial number of replications (n_0) and one-time computing budget increment (Δ) should be selected with care. Because the selection of a very small n_0 will result in poor estimation of mean and variance, in our experiments n_0 is chosen to be 5, 10, and 20 (replications) for 1-MG, 2-MG, and 3-MG, respectively. Similarly, the tradeoff between the magnitude of Δ and accuracy of estimation in $P\{CS\}$ should be considered as large Δ values may result in poor estimation of $P\{CS\}$ while small Δ values may result in frequent budget allocation problems, such as large number of iterations and slow growth in P{CS}. To this end, based on the number of fidelities, Δ is decided upon as

10, 25, and 500 for 5, 25, and 125 fidelities. Based on the aforementioned initial settings, the results for the different networking structures are presented below.

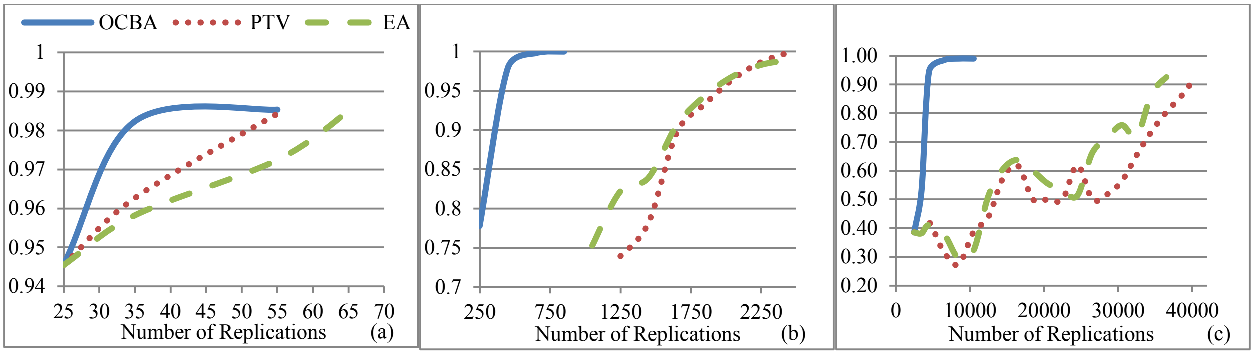

Figure 4: $P\{CS\}$ comparison of OCBA, PTV and EA for 1-MG (a), 2-MG (b), and 3-MG (c).

Experiments with 1-MG network: This scenario includes only one independent MG with 5 designs, where $n_0 = 5$ and $\Delta = 10$. The results of this experiment show that the OCBA algorithm obtains a probability of correct selection of 98.5% after 35 replications (see blue line in Figure 4(a)). The same probability of correct selection is obtained in 55 and 65 replications when PTV and EA algorithms are applied, respectively (see green and red lines in Figure 4(a)). Therefore, the OCBA algorithm applied to 1-MG network reached the desirable correct selection probability (over 98%) approximately 60% and 85% faster than those of PTV and EA algorithms respectively. Here, the best design for the 1-MG network structure is selected as MG1 – F3 (fidelity 3), as it has the highest performance among its alternatives.

Experiments with 2-MG network: This scenario is a larger scale version of 1-MG experiment which includes two independent MGs with five different levels of fidelity for each, where $n_0 = 10$ and $\Delta = 25$. Due to the size of this problem (25 designs), the initial probability of correct selection (P{CS}) is smaller. The result obtained from the 2-MG network in Figure 4(b) reveals that the OCBA algorithm reaches the 97.9% and 99.8% probability of correct selection after 500 and 750 replications, respectively, (see blue line in Figure 4(b)). On the other hand, using PTV and EA algorithms results in the same P{CS} after 2250 and 2500 replications, (see red and green lines in Figure 4(b)). These results indicate that using OCBA for finding the best design with high probability of correct selection applied on our 2-MG structure is four times faster than PTV and EA. The results also reveal that the design having both microgrids in fidelity 3 (MG1 – F3 , MG2 – F3) has the highest performance among the alternatives.

Experiments with 3-MG network: This scenario is the largest MG structure tested and includes 125 alternative designs (5 designs for each MG) which make the problem more complex due to the severely high number of computations necessary. Comparing the OCBA algorithm in selecting the best design for the 3-MG experiment against PTV and EA will illustrate in the most robust way the dominance of OCBA over the other algorithms. Since there are 125 designs in this experiment, to avoid poor estimation for P{CS}, the initial parameters for this experiment are set to $n_0 = 20$ and $\Delta = 500$. The results for the three different algorithms depict that the speed up factor of using OCBA in 3-MG structure with several alternative designs is increased more than the 1-MG and 2-MG problems. Figure 4(c) shows that OCBA meets the 94.5% and 98.45% probability of correct selection after 4500 and 6500 replications respectively. On the other hand, using EA and PTV algorithms, the 93% correct selection probability is reached after 36500, and 40500 replications respectively. Consequently, the best design for 3-MG networking structure is selected with a high probability of correct selection 9 times faster using OCBA, which reveals that the OCBA algorithm is more efficient than EV and PTV in selecting the most appropriate level of control, in an MG environment. The results also conclude that the design which has all MGs in fidelity 3 (MG1 – F3, MG2 – F3, MG3 – F3) has the highest performance among those tested.

For sensitivity analysis purposes, we also compared the three algorithms using a different set of coefficients for the objective function. In all cases the OCBA dominates the other algorithms in terms of the number of replications. This is shown to be especially true when the number of alternative designs is high (3-MG network). The only difference in these cases is the outcome of the best selected design. When the cost is assigned a larger weight in the objective function, the best scenarios are the ones with lower fidelities in general (less control points in the network).

5 CONCLUSION AND FUTURE WORK

In this paper, a simulation based optimization method, namely optimal computing budget allocation method, is investigated and is found to facilitate and significantly speed up the selection of the best control design in MG simulations in terms of cost and demand surety. The multi-criteria nature of the considered problem is captured via a weighted single objective, namely MG performance function, reflecting a desirable part of Pareto frontier with predetermined priority of objectives. In order to discover the best simulation design in MG networks, different ranking and selection methods comprising OCBA, Equal Allocation (EA), and Proportional to Variance (PTV) have been applied and compared. The results for the design ranking and selection amongst the simulations have shown that the design selection using the OCBA algorithm can reduce the total simulation replication time up to 9 times (with about 36000 fewer replications) when compared with the Equal Allocation (EA) and Proportional to Variance (PTV) methods. While the current work is focused on energy surety maximization and cost minimization objectives of this network, several additional objectives, such as minimization of emission and maximization of security and cyber-security, could be considered in the future. However, as the number of considered objectives increases, the accuracy of measured performance of the system through the developed evaluation function is expected to decrease due to the augmented degree of uncertainty.

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