Towards Real-time Microgrid Power Management using Computational Intelligence Methods

C.M. Colson, *Student Member, IEEE,* M.H. Nehrir, *Senior Member, IEEE,* and S. A. Pourmousavi, *Student Member, IEEE*

***Abstract*—Microgrids are an emerging technology which promises to achieve many simultaneous goals for power system stakeholders, from generator to consumer. The microgrid framework offers a means to capitalize on diverse energy sources in a decentralized way, while reducing the burden on the utility grid by generating power close to the consumer. As a critical component to enabling power system diversity and flexibility, microgrids encompass distributed generators and load centers with the capability of operating islanded from or interconnected to the macrogrid. To make microgrids viable, new and innovative techniques are required for managing microgrid operations given its multi-objective, multi-constraint decision environment. In this article, two example computational intelligence methods, particle swarm optimization (PSO) and ant colony optimization (ACO), for application to the microgrid power management problem are introduced. A mathematical framework for multi-objective optimization is presented, as well as a discussion of the advantages of intelligent methods over traditional computational techniques for optimization. Finally, a three-generator microgrid with an ACO-based power management algorithm is demonstrated and results are shown.**

***Index Terms* – Distributed generation, Intelligent control, Microgrids.**

I. INTRODUCTION

Overwhelmingly, nations of the world derive their electricity from centralized generation. Global electricity generation is projected to increase 2.4% each year, from 16,424 billion kWh in 2004 to 30,364 billion kWh in 2030 [1, 2]. As demand continues to rise, increased pressure will be placed on existing central power plants, transmission assets, and distribution systems. This steadily escalating need for electrical power, progress in power deregulation, tight construction constraints on new high voltage long distance power transmission lines, and reliance on central generation places the nation's energy future in a difficult predicament. Recognizing the challenges facing centralized electricity generation, along with growing global environmental concerns, interest has increased for alternative energy (AE) generation. Many AE devices are attractive primarily because of low or zero emissions, high efficiency, scalable application, and/or adaptability to remote implementation. It is believed that these desirable characteristics can be capitalized upon through hybrid combination of AE sources, networked within a microgrid framework to significantly improve their reliability and better deliver power close to customer loads. Although inherently adaptable to islanded (separated from the macrogrid) applications, it is expected that alternative energy distributed generation (AEDG) microgrids that capitalize on diverse energy sources, are controlled in a decentralized way, and reduce the burden on the utility grid will penetrate the existing infrastructure network in the near future [3].

There is no standardized definition for what comprises a microgrid. However, general consensus specifies a microgrid as a small-scale power system that has three primary characteristics: distributed generators, autonomous load centers, and the ability to operate connected to or independently from the utility power system. Interest in the microgrid concept, at the distribution level, with multiple AEDG sources has been increasing worldwide [4-7]. The promise of implementing scalable microgrid generators that can be coordinated and controlled in a decentralized way is desirable for many consumers. Ultimately, the primary goal for microgrid architectures is to significantly improve energy production and delivery for load customers, while facilitating a more stable electrical infrastructure with a measurable reduction in environmental emissions.

The following paper seeks to introduce emerging computational techniques for intelligent power management of microgrids for the purpose of making progress towards their integration and implementation into the power system. Specifically, two representative emerging intelligent methods, particle swarm optimization (PSO) and ant colony optimization (ACO) are presented. The challenges associated with multi-objective optimization, along with two alternative, computationally intelligent methods for addressing those challenges and a simulated implementation are presented in five sections. A discussion of the computational framework for optimization is presented in Section II. The two intelligent methods, PSO and ACO, as well as their advantages over traditional methods for solving optimizations, are presented in Section III. An example of a microgrid power management optimization using an ACO is shown in Section IV. Finally, conclusions are given in Section V.

II. COMPUTATIONAL CHALLENGES FOR OPTIMIZATION

The practice of decision-making is a very familiar process for humans. However, attempting to codify the decision-making process in a meaningful, efficient, and useful way is often very challenging. Subsequently, implementing effective autonomous decision-making for automated systems can be

C.M. Colson (email: christopher.colson@msu.montana.edu), M.H. Nehrir (hnehrir@ece.montana.edu), and S. A. Pourmousavi (s.pourmousavikani@montana.edu) are with the Electrical & Computer Engineering Dept, Montana State University, Bozeman, MT 59717 USA.

978-1-4244-6551-4/10/$26.00 ©2010 IEEE

difficult. Additionally, implementation is complicated by the need to make judgments rapidly and to seek an ideal conclusion amongst a field of many options and factors. The microgrid power management system is an example of an automated decision-making framework that must comprehensively consider complex factors that affect a complex system. This section intends to highlight the unique challenges faced by the microgrid power management system and elucidate the structure of the problem it seeks to optimize.

Typically, when attempting to decide between simple options, say whether to purchase a bus ticket or walk to a destination, there is often more than a single factor that influences the decision. In this way, the travel choice via bus or on foot can be considered the "variable" which has two possibilities, or a "domain" of two. However, many related "constraints" may exist, such as: available change to pay the cost of the bus ticket, time allowed to reach the destination, etc. Assuming that decisions are made towards a certain goal or collection of goals, this interrelated combination of variables, their domains, and constraints are compiled according to the decision-making framework towards the development of a solution. In this broad context, the process of evaluating decision components and seeking the best solution available is incorporated within the extensive field of optimization analysis. In optimization, when objectives are described as mathematical formulations, a single or multiple objective functions may result. Although many possible solutions exist within the space of possibilities, the ultimate prize is the single solution that either "maximizes" or "minimizes" the objective function across all possible solutions. In other words, when an objective function is maximized or minimized, it has achieved the largest possible "satisfaction" for the decision-maker. In a local solution space, the solution that is the best of all local possibilities is considered the "local" best; the solution that is the very best of all possible solutions across the entire solution space is considered the "global" best.

Often, decision-making situations arise that require analysis of numerous competing objectives, simultaneously. The pursuit of an ideal solution given this more complex scenario is described as a multi-objective optimization, where the goal is to seek an optimal solution amidst many objectives. In such problems, the satisfaction of the objective functions becomes a combination of vector "maximizations" or "minimizations". However, in most cases, a global best of any particular individual objective function may not be a satisfactory solution for the remaining objectives [8]. Because of this, we need to alter our concept of optimality for such problems. In a similar manner as with economic systems, a Pareto optimum can be reached where the solution represents a state of satisfaction for one objective that cannot be raised further without lowering another objective's satisfaction. In other words, many "optimal" solutions exist when considering multiple objectives. The mathematical expression for this problem takes the form of:

$$\text{min/max}\, F(\vec{x}) = \left[f_1(\vec{x}),\, f_2(\vec{x}),\, \cdots,\, f_m(\vec{x})\right],$$
$$\vec{x} = \left[x_1,\quad x_2,\quad \cdots\quad x_n\right]^T \in R^n \tag{1}$$

Subject to:

$$G(\vec{x}) \le 0\ ,\ G = \left[g_1,\quad g_2,\quad \cdots\quad g_p\right]^T \tag{2}$$

$$H(\vec{x}) = 0\ ,\ H = \left[h_1,\quad h_2,\quad \cdots\quad h_q\right]^T \tag{3}$$

where, F is the vector of objective functions containing m objective functions (f_1 to f_m), $\vec{x}$ is the n-length vector of variables to be optimized known as the decision variables, G represents the p-length vector of inequality constraints, and H represents the q-length vector of equality constraints. The relationship between two decision variables, three constraints, and two objective functions are shown in Fig. 1. A particular solution of decision variables maps to the graph of the objective functions. The Pareto frontier, or front, represents the combinational minimization of the two objective functions, and is shown by the dark line in Fig. 1.

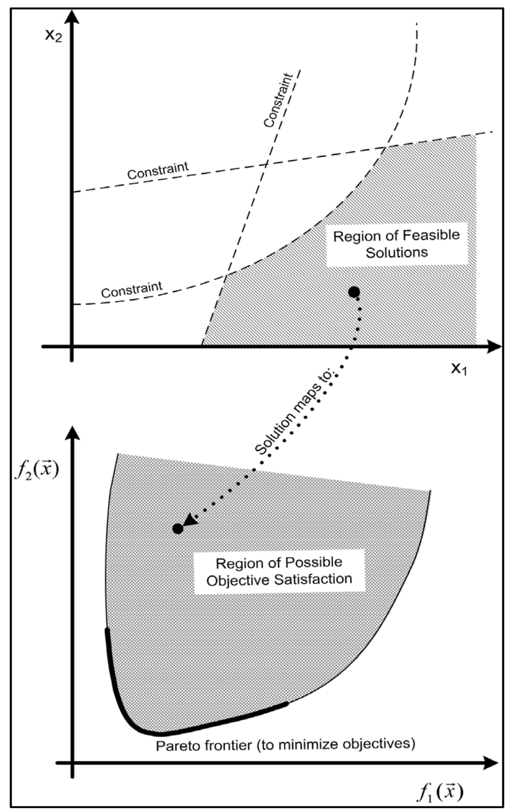

Fig. 1. Representation of a multi-objective, multi-constraint optimization problem and resulting Pareto frontier.

As is described above, there are no direct methods for developing the solution set that lies along the Pareto front. However, two primary formal mathematical techniques exist to derive Pareto solutions. The first technique involves aggregating the various objective functions into a single objective function expression [9]. In effect, by combining objective functions, the issues of simultaneously handling multiple objective functions is side-stepped. This technique is relatively simple and based on traditional gradient-based methods, but requires the decision-maker to assign the relative weights of the constituent objective functions within the aggregation. The second broad category for addressing multiple objectives involves the class of intelligent methods. The intelligent methods category incorporates a diverse range of techniques including: evolutionary, heuristic, and non-classical algorithms. The primary advantage of these intelligent methods is that they can address many objective functions simultaneously while requiring less computational resources to derive solutions in less time [10].

For more than a decade, intelligent methods have proven themselves for a variety of computational challenges. Power management of microgrid operations clearly fits into the broad field of multi-objective optimization problems of interest today. The mathematical class of multi-objective optimization problems has not been proven to be solvable in strongly polynomial-time, or in other words, present verifiably global solutions rapidly. Because of the slower nature of traditional iterative techniques, alternative intelligent methods have shown promise. Ultimately, the interest in computational alternatives to traditional iterative techniques is manifested by the desire to derive near-optimum results in short periods of time [11]. Therefore, their application to microgrids for real-time power management is a ready area of challenge.

The formulation of the multi-objective, multi-constraint microgrid power management problem begins by identifying the desired attributes of the microgrid. These factors encompass many of the objectives currently sought by the power system, but go beyond conventional operations in many key ways. Inherently, these objectives are entirely dependent upon the relative importance to the consumer, but the following objectives are split into major and minor categories for the purpose of further discussion:

Major objectives:

- Maximize the customer's power availability (e.g. meet consumer's instantaneous load demand)
- Minimize economic factors (i.e. fuel costs, operation and maintenance, start-up/shut-down costs, etc.)
- Minimize environmental impact from operating microgrid generators (e.g. emissions, noise, hazardous waste, etc.)
- Maximize the dispatch of shedable loads (e.g. loads capable of reacting to demand response signals)
- Maximize revenue derived from service delivery to the utility grid (including ancillary services, reserves, etc.)
- Minimize energy purchased from outside microgrid
- Maximize the total efficiency of the microgrid (e.g. kWhrs generated versus kJ fuel consumed)
- Maximize capitalized energy sources (e.g. operational efficiency of kWhrs available versus kWhrs generated)
- Minimize the number of power reversals across the grid interconnection
- Minimize transient periods during stabilization in the event of a casualty or interruption

Minor objectives:

- Maximize load factor (e.g. smooth out the peaks and valleys of load and subsequently required generation)
- Minimize the need for storage assets
- Maximize the microgrid capability to reduce strain on distribution and transmission assets
- Maximize VAR support to the greater power system
- Maximize the reduction in line losses
- Allow the stable, seamless, and adaptable integration of generation and load assets onto the microgrid (also known as "plug-and-play")

In addition to these objectives, the microgrid primary constraints are:

- Availability of renewable resources (i.e., solar insolation, wind energy, etc.)
- Bus voltage, frequency, and stability requirements
- Physical electrical characteristics of the microgrid
- Status of interconnection

Clearly, this is a complicated problem. Often one or more of the objectives described are in direct conflict with other objectives. Additionally, it should be noted that both the constraint and objective functions for the microgrid power management problem have been shown to have non-linear, non-homogenous, and time-varying characteristics. While it may be possible to linearize many of these functions, it is not desirable to do so. Based on the complexity of the problem, there is a strong need for rapidly converging computational techniques capable of determining near optimal solutions without the dependence on computationally expensive methods [12].

III. Two Intelligent Methods for Optimization

A. Predominant Research

To date, the majority of power system research applications utilizing intelligent computational methods have primarily investigated off-line problem solving [13-21]. This involves the use of computational resources to solve a problem, not in real-time, and have those solutions used later. These previous works have demonstrated the effectiveness of computational intelligence methods for power system application. In this paper, however, we seek to build upon prior research to support the concept that these techniques can be used for both off-line and real-time applications. The ultimate advantage of applying intelligent methods to the microgrid power management problem is to capitalize on their most powerful demonstrated property: rapid convergence. That characteristic, coupled with the capability of computationally intelligent methods to handle multiple objectives simultaneously makes them of considerable interest for microgrid power management.

B. Particle Swarm Optimization (PSO)

The PSO computational method was inspired by biological social swarming behavior such as exhibited by birds flocking or fish schooling. Since its introduction in 1995, PSO has been shown as a powerful tool for solving many classes of problems including nonlinear optimization, control, and artificial intelligence [12, 22-24]. PSO is amongst the heuristic class of intelligent methods and it shares many similarities with evolutionary computation techniques such as genetic algorithms (GA). However, PSO is easier and faster to implement PSO than GA in that the former does not have evolutionary operators such as crossover and mutation. Similar to other evolutionary algorithms, PSO requires a fitness evaluation function assesses each solution according to its value. At each iteration, the solution developed with the highest fitness value amongst all solutions thus far developed is retained as the global best. PSO is an iterative method, so the best retained solution at the end of assigned iterations is returned as final best solution.

The primary premise of PSO is the use of computational entities, referred to as agents, which are distributed throughout the search space. Within the search space, each positional location represents a solution to the posed problem. Each agent is initialized with a random position and random velocity. At each computational increment, the agents travel through the search space, checking the fitness of each position they traverse. They retain information about the best location (P_{best}) they have visited. Additionally, by communicating information about their search results to the total swarm of agents, the collective group can converge upon the globally best solution within the available possible solutions. At each increment in computation, each agent within the n-dimensional search space has their velocity accelerated towards the swarm's global best and the local agent's personal best position based on the following equation [24]:

$$v_j^{t+1} = \omega . v_j^t + c_1 . rand . (P_{best,j} - s_j^t) + c_2 . rand . (G_{best} - s_j^t) \quad (4)$$

where: v_j^t is the velocity of agent *j* at iteration *t*, c_1 and c_2 are weighting factors which can be fixed or changed during iterations, *rand* is a random number between 0 and 1, s_j^t is the current position of agent *j* at iteration *t*, $P_{best,j}$ is the personal best value of agent *j* so far, $G_{best,j}$ is the swarm's best solution so far, ω is the inertial weight of the agent. Upon each successive iteration, the search position (s_j) of each agent is obtained by the following equation [24]:

$$s_j^{t+1} = s_j^t + v_j^{t+1} \quad (5)$$

At the beginning of the search, the inertial weight of each agent within the swarm is large to cause greater exploration of the solution space. As the number of iterations increases, inertial values decrease allowing the agents to better converge on the "best" solution. The process for steering the agent particles as they travel through the search space according to Eq. (4) is illustrated in Fig. 2.

As a computational technique, PSO is well-suited for handling multi-objective optimization problems. In the microgrid formulation, solutions that satisfy simultaneous objectives, and therefore define the Pareto optimal set, must be found from an expansive set of possibilities. The PSO algorithm, because of its strong search capabilities and quick convergence upon best solutions, can be used to rapidly find the Pareto set. These characteristics make it of keen interest for addressing the temporal demands imposed by performing microgrid power management in real-time.

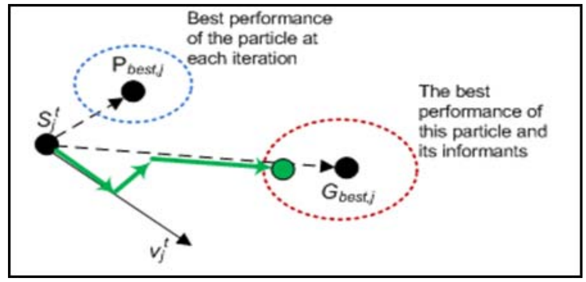

Fig. 2. How the position of the search agent, represented as a particle, is modified based on the PSO algorithm.

C. Ant Colony Optimization (ACO)

The ACO algorithm is also a nature-inspired metaheuristic optimization method, proposed by Dorigo, et al. [11], for solving NP-hard combinatorial optimization problems such as the benchmark traveling salesman problem (TSP), scheduling problems, subset problems, and a host of others. This intelligent computational technique is of particular interest because it has been shown to develop Pareto-optimal solutions with short time complexity [25]. Additionally, the ACO algorithm has been shown to outperform other general purpose optimization algorithms including genetic algorithms (GA) when applied to a number of benchmark combinatorial optimization problems, although this claim is widely interpretational [11]. The ACO algorithm has been investigated for power system-related applications, but exclusively for off-line computation only [13, 16, 26-30].

Within the ACO algorithm, colonies of artificial ants cooperate in a similar manner as PSO, to search the space of possible solutions to find the ones that are optimal. However, the framework for ACO is very different than PSO, as well as the use of heuristics to guide searching. The mathematical formulations for optimization problems are generally represented within ACO as construction graphs, where each node in the graph corresponds to a component of the solution. The goal is to find the solution with the minimum cost or distance path, which ultimately represents the best solution. Each ant "walks" on this graph and incrementally builds a solution. In this way, ACO is different from PSO in that at each computational increment, the PSO particle calculates the fitness of an actual problem solution. In ACO, each node represents an incremental part of the actual problem solution and it is not until after an ant has completed their "walk" that an actual solution is available. Modeled after real ants, the behavior of the artificial ants is governed by two primary factors: stigmergic tendency and random exploration. Stigmergy, or indirect communication facilitated by the environment, is accomplished in nature through the deposit of chemical pheromones. The pheromones reinforce good solutions and guide the search. For the ACO algorithm, a simulated ant uses artificial pheromones at each step in the construction graph, along with other problem specific heuristics, to randomly select the next solution component.

The algorithmic framework for ACO depends on the construction graph representation, is typically simplified as: G = (N,A,C). For the graph G, the set of nodes N = $\{d_1, d_2, \ldots, d_n\}$ represents where path decisions must be made; the set of arcs A = $\{l_{ij}\}$ link the nodes i to j; and (optionally) C = $\{c_{ij}\}$ is the set of costs associated with arcs A. The elements of sets N and A are typically constrained. Depending on the particular problem formulation, the order of the solution sequence is not important. Fig. 3 shows an example of a construction graph that the ACO algorithm would attempt to solve. Nodes d_1 through d_3 are shown in Fig. 1, as well as how additional nodes (d_n) would be added to the construction graph. A complete path on the graph passes through each node once, contains a set of arcs (represented as dashed lines in Fig. 4), and is called a solution (s). The minimum cost path is called the best solution (s*) and is represented by the darkened arcs in Fig. 4 as the shortest complete path, and thus the best solution.

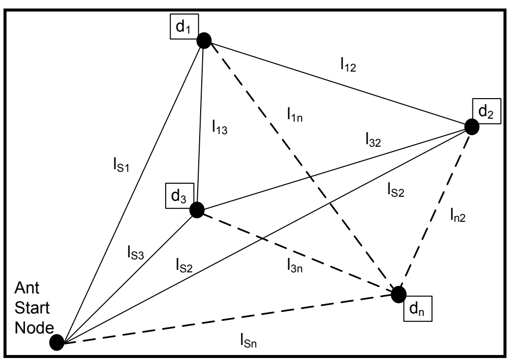

Fig. 3. Typical ACO construction graph framework.

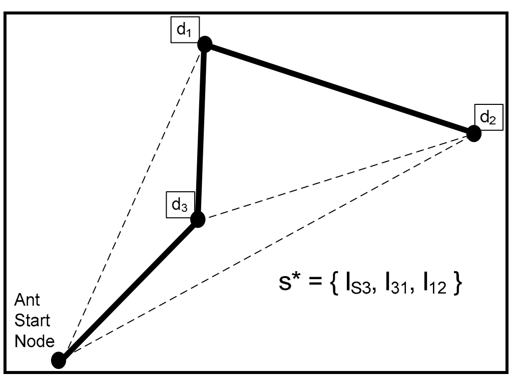

Fig. 4. Optimal solution (s*) representation.

The path an ant takes is constructed based on a probabilistic function. At each construction step, an ant must "choose" the next node to visit in pursuit of a complete solution. The probability of choosing node j from node i, is a combination of pheromone weighting and random exploration, expressed by:

$$p_{ij}^{k} = \frac{[\tau_{ij}]^{\alpha}[n_{ij}]^{\beta}}{\sum_{l \epsilon N_i^k}[\tau_{il}]^{\alpha}[n_{il}]^{\beta}} \tag{6}$$

where: τ_{ij} is the pheromone on arc ij, α is the pheromone weighting factor, n_{ij} is the heuristic value on arc ij, β is the heuristic weighting factor, and N_i is the feasible neighborhood of options for the ant, *k*, to traverse from node i. In addition to global heuristics that help improve the simulated ant's capabilities, pheromones associated with the construction graph are "deposited" on the arc chosen and globally "evaporate" over time. Pheromone decay on the construction graph arcs are accomplished by:

$$\tau_{ij}^{f} = (1-\rho)\tau_{ij}^{o} \tag{7}$$

where: τ_{ij}^{o} is the current step pheromone value on arc ij, τ_{ij}^{f} is the updated pheromone value on arc ij, and ρ is the decay factor. This combined effect allows for the artificial stigmergic effect which leads to better solution convergence.

As with PSO, there are numerous modifications to the ACO algorithm that can be made to allow customization for particular problems. Specific heuristics and factors such as the number of particles or ants per iteration, as well as the influence of inertia, pheromones, and decay affect the speed and accuracy of the solutions derived. In a similar manner to PSO, ACO can outperform gradient-based methods when faced with multi-objective optimization problems. The ants of ACO can find solutions that satisfy many simultaneous objectives rapidly and minimizing computational resources. As with PSO, the computational characteristics that make ACO attractive for deriving Pareto optimal solutions make it desirable for addressing the diverse objectives and constraints inherent to power management for the microgrids.

D. Advantages of Intelligent Methods over Traditional Computational Techniques for Optimization

The multi-objective optimization problem for microgrid power management is not expected to be solvable in polynomial-time. Therefore, as the complexity and size of the search space broadens, along with the consideration of multiple objectives, computational techniques such as PSO and ACO are expected to perform significantly better than traditional gradient-based optimization methods. This is primarily because of the computational expense suffered by traditional means of solving optimization problems. For gradient-based methods, including Newton's method, the set of first-order partial derivatives of the objective function, called the Jacobian matrix, must be obtained. In some cases, the set of second-order partial derivatives, called the Hessian matrix, or an approximation of it, must also be obtained. Finding the inverse of a matrix of appreciable size requires a significant amount of computational time and resource. On the other hand, computationally intelligent methods do not explicitly derive large matrix inverses because they remain within the search domain only. The result from attacking the optimization problem with ACO or PSO is a much more rapid convergence to a near-optimal solution, especially as the complexity of the microgrid problem grows.

In addition to computational burdens, when seeking a solution, gradient-based methods rely heavily on an initial guess of the solution. Correspondingly, they suffer from pitfalls which may lead them towards local best solutions rather than global best solutions. Alternatively, the general performance of the PSO and ACO algorithms is independent of the quality of particle or ant initialization. Inherent to intelligent methods are heuristical and stochastic terms that minimize the possibility of the search becoming fixed upon a solution that is not globally best.

For any computationally intelligent method, there will always be practical and theoretical tradeoffs that are incorporated into the algorithmic formulation. For example, the choice of how many ants per colony, or how many particles per stage, directly affects solution development. It is difficult to know, except through experience and educated-guessing how to best formulate the intelligent method for a particular problem. While these are practical considerations for the development of computationally intelligent methods, they offer the opportunity to tune the algorithms in more customizable ways than with traditional methods.

IV. Example of a Microgrid Power Management Optimization Using an Intelligent Method

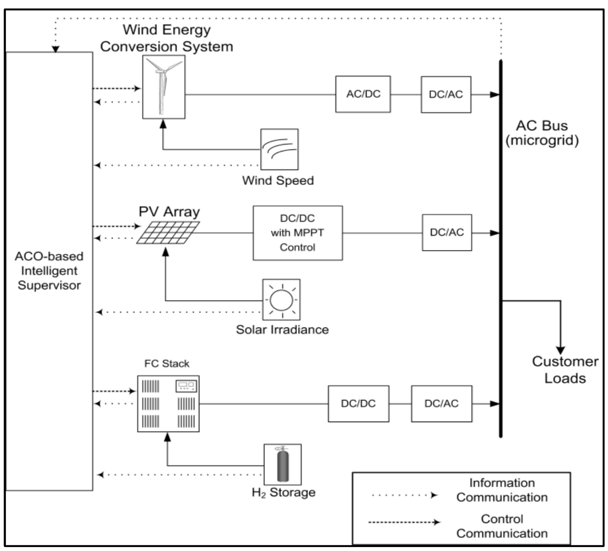

Fig. 5. Simulated microgrid and ACO-based power management supervisor.

Using a simple three-generator hybrid microgrid framework, shown in Fig. 5, an intelligent power management system was developed and evaluated. By using information about generator characteristics, resource availability, and power demand, the ACO-based power management algorithm sought optimal dispatch solutions given two objectives: minimize environmental emissions and minimize the cost of generation. The primary constraints were dictated by the generator characteristics, power flow characteristics, and a 0.05 per unit deadband about the microgrid bus voltage, to which the customer load is connected. The customer load was modeled as a constant impedance; the changes in power consumed by the load were dictated in simulation by changing load current. The electrical configuration for the simple microgrid is shown in Fig. 6.

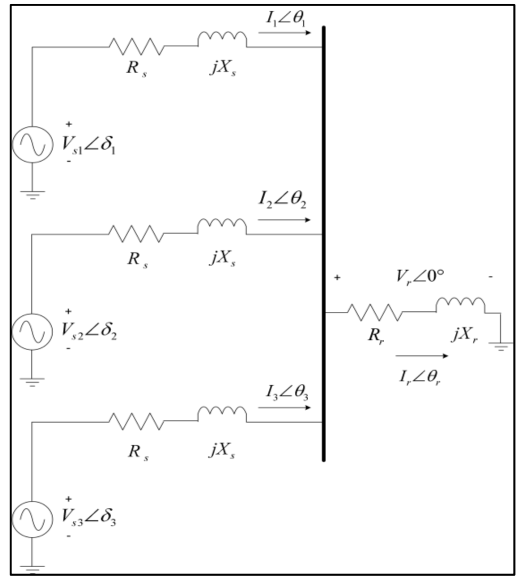

Fig. 6. Simulated three-generator microgrid electrical configuration.

The power management algorithm looked at the conditions on the microgrid in 30-second snapshots. At each sampling instant, the power management algorithm perceived power demand and the local conditions (e.g. wind speed, solar insolation) that dictated the ability of the renewable generators to produce power. Based on this information, the algorithm (within the sampling interval) developed and searched the construction graph for optimal dispatch solutions for the three microgrid generators. The mathematical formulation of the optimization problem is shown in equations (8)-(14), below:

Minimize:

$$\sum_m f_{1,m}(\sigma_m, V_m) = E_m \text{ \{Environmental Objective\}} \quad (8)$$

$$\sum_m f_{2,m}(\mu_m, V_m) = C_m \text{ \{Cost Objective\}} \quad (9)$$

Subject to: $$V_{deadband}^{low} \leq V_r = Z_r I_r \leq V_{deadband}^{high} \quad (10)$$

Given: $$I_1 + I_2 + I_3 - I_r = 0 \quad (11)$$

$$V_{sm} - V_r = Z_m I_m \quad (12)$$

$$Z_1 = Z_2 = Z_3 = Z_s \quad (13)$$

$$P_m = f_{p,m}(V_m) \quad (14)$$

where: m is the generator index, f_1 and f_2 are the objective functions, σ is the environmental impact factor, V is the nodal voltage, μ is the cost factor, Z is the component impedance, I is the branch current, and P is the instantaneous power generated by the generator, as determined by f_p. The voltage V_{sm} refers to the sending voltage of generator m; V_r refers to the receiving bus voltage to which the customer loads are connected. Both σ and μ factors are functions of the operating point of the given generator, e.g. the operating cost of the fuel cell is based on the fuel it consumes at a given output power.

Established by equations (8)-(14) and the known generator characteristics, the construction graph was formed, shown in Fig. 7. During the sampling interval, the ACO-based algorithm searched the construction graph for the optimal dispatch solution of each generator. The construction graph contained a node ($x_{sm,n}$; where, *sm* is the specific generator and *n* is the node index) for every possible variable assignment ($V_{n,sm}$). In other words, the construction graph represents the entire scope of available operating conditions for the microgrid, during a sampling interval; each node represents an operating point for an individual generator and its associated objective function values ($f_{1,sm}$ and $f_{2,sm}$). The graph is fully connected except for nodes of the same generator (e.g., $x_{s1,1}$ cannot be connected to $x_{s1,2}$). This prescribed constraint enforces the stipulation that only one instantiation for each variable (variable selection) is allowed in a solution set. For the microgrid power management formulation, this is analogous to selecting one operating point for an individual generator (it is invalid to select two or more operating points for the same generator). Only one generator operating characteristic was modeled for this example (e.g., voltage), but there is no limit to generator properties, such as frequency, that can be added as domains in this formulation. The ants walk the graph until a value has been selected for each variable, resulting in dispatch positions for each generator attached to the microgrid. Stigmergic information relating to the best solutions developed by colonies of ants was retained between sampling instances, although decayed over time, on the construction graph. This improved the ants' performance upon subsequent sampling intervals because lower fitness solutions were discriminated against. Although the search space is large, the constraints trim the construction graph preventing the inclusion of every possible variable assignment. It should be noted that not all nodal connections are indicated on the construction graph in Fig. 7 for clarity.

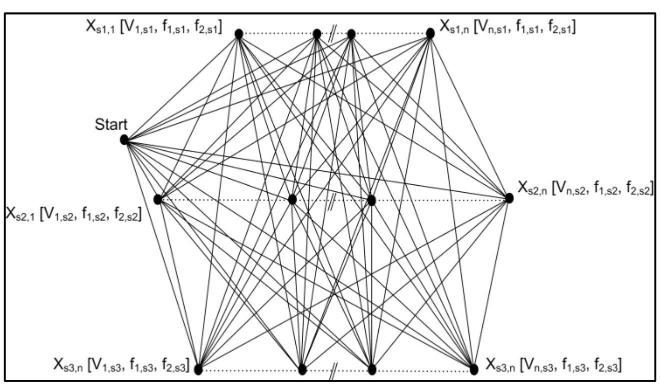

Fig. 7. Construction graph used by ACO-based power management algorithm.

Using the ACO-based power management algorithm for the three-generator microgrid, Pareto-optimal dispatch solutions were developed during each sampling interval. A typical result based on the resource availability at a sampling instance is shown in Fig. 8. In Fig. 8, the power characteristic curves for each microgrid generator are shown, as well as the best operating power points for each generator selected by the power management algorithm after searching the construction graph. Results similar to those shown in Fig. 8 were produced during each sampling interval facilitating near real-time power management for the simulated microgrid.

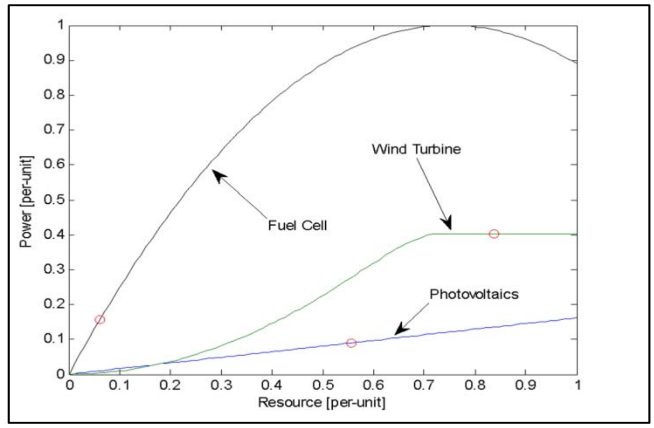

Fig. 8. Typical results from the power management algorithm for generator dispatch based on available resources.

One of the primary reasons intelligent methods are of interest for microgrid multi-objective optimization is the desire to derive solutions quickly, facilitating real-time power management. Towards this goal, the ACO-based algorithm functioned well and after a series of experiments, its performance was characterized, as shown by Figs. 9 and 10. Simulation results show that in this case, there was not a direct correlation between increasing the computational resources (e.g. the number of ant colonies that search the construction graph) and the achievement of corresponding gains in finding better solutions. In other words, as shown by Fig. 10, given a fixed number of computational iterations, significant improvement in the satisfaction of the objectives was not achieved by utilizing more than 5-20 colonies of 50 ants. Simply put, the considerable additional time spent by more than 5-20 colonies of ants searching for better solutions does not show great benefit. This is not a new discovery [11, et.al.] and supports the concept of tuning the algorithm for the particular application. Moreover, by using 5-20 colonies of 50 ants per colony, strong solutions for the microgrid power management problem could be derived within the 30-second sampling interval. The ability to find near-optimal solutions quickly represents a significant result towards achieving solutions truly in real-time.

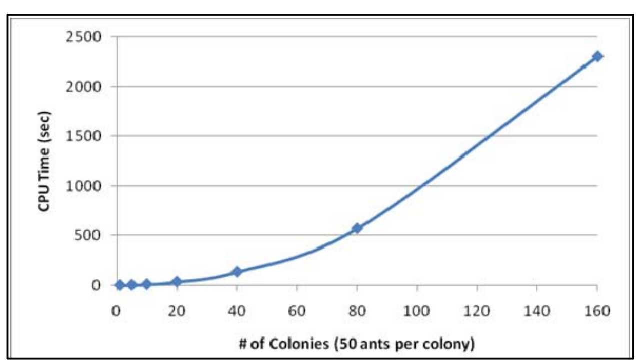

Fig. 9. Computational time required by increasing the number of colonies used by the power management algorithm.

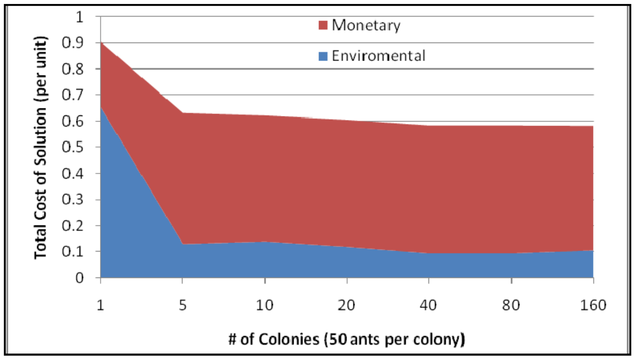

Fig. 10. Average performance (five runs) of the power management algorithm towards achieving given objectives based on a fixed number of computational iterations and varying the colonies parameter.

V. CONCLUSION

The efforts to prepare for the energy future will likely include measures to modernize the electrical grid, enhance the quality and reliability of the energy supply, diversify how the nation sources its immense hunger for electricity, and address the looming crisis of environmental impact of emissions from energy consumption. Microgrids are a logical choice for achieving these goals. However, in order for microgrids to become widely implemented and meet the comprehensive challenges set forth, they must have a robust and rapid means of managing the power generated and consumed within the microgrid framework. Not only the quality of the solutions, but the speed at which they are obtained, are critical factors when selecting the computational method for driving microgrid power management.

In this paper, a multi-objective, multi-constraint optimization framework has been discussed. The objectives and constraints for the microgrid power management problem have been introduced based on this framework, as well as two example computationally intelligent methods for seeking Pareto optimal solutions. Algorithmic details for the two methods and their advantages over traditional gradient-based techniques have been shown, as well as the performance of an simulated microgrid implementation. The microgrid power management problem is complicated greatly by the demand for robust and rapid solutions; the case for the use of computationally intelligent methods to address this challenge has been presented herein.

REFERENCES

[1] Energy Information Administration - Office of Integrated Analysis and Forecasting, "Annual Energy Outlook 2006", DOE/EIA-0383, 2006, available at: http://www.eia.doe.gov/oiaf/ieo/index.html.

[2] United States Energy Information - Office of Integrated Analysis and Forecasting, "International Energy Outlook 2007", DOE/EIA-0484, 2007, available at: http://www.eia.doe.gov/oiaf/ieo/index.html.

[3] N. Hatziargyriou, H. Asano, R. Iravani, and C. Marnay, "Microgrids," *IEEE Power & Energy Magazine*, Vol. 5, Issue 4, July/August 2007.

[4] R. Lasseter, A. Abbas, C. Marnay, J. Stevens, J. Dagle, R. Guttromson, A. Sakis Meliopoulos, R. Yinger, and J. Eto, "Integration of distributed energy resources: The CERTS microgrid concept," California Energy Commission, P500-03-089F, Oct. 2003.

[5] Y. Fujioka, H. Maejima, S. Nakamura, Y. Kojima, M. Okudera, and S. Uesaka, "Regional power grid with renewable energy resources: A demonstrative project in Hachinohe," *CIGRE 2006*, Paris, August 2006.

[6] B. Bucholz, et al, *PE Magazine*, July/August 2007.

[7] European Commission (Apr. 2006), "European SmartGrids technology platform: Vision and strategy for Europe's electricity networks of the future", (http://ec.europa.eu/research/energy/pdf/smartgrids_en.pdf).

[8] Saul Gass, Linear Programming: Methods and Applications - 5th Edition, Dover Publications, Inc. 2003, pgs. 224-250.

[9] A. Osyczka, "Multicriteria optimization for engineering design", Design Optimization edited by J. Gero, Academic Press Inc., 1985.

[10] C.M. Fonseca & P.J. Fleming, "Multiobjective optimization and multiple constraint handling with evolutionary algorithms - Part I: a unified formulation", *IEEE Transactions on Systems, Man, and Cybernetics Part A:Systems and Humans*, Vol. 28, No. 1, Jan 1998.

[11] M. Dorigo and T. Stutzle, Ant Colony Optimization. MIT Press, 2004.

[12] K.Y. Lee and M.A. El-Sharkawi, Modern Heuristic Optimization Techniques – Theory and Application to Power Systems, IEEE Press, Piscataway, NJ, 2008.

[13] P. Korosec and J. Silc, "The distributed multilevel ant-stigmergy algorithm used at the electric-motor design" *Engineering Applications of Artificial Intelligence*, Vol. 21, No. 6, September 2008.

[14] M. Lopez-Ibanez, T.D. Prasad, B. Paechter, "Ant colony optimization for optimal control of pumps in water distribution networks" *Journal of Water Resources Planning and Management*, Vol. 134, No. 4, July/August 2008.

[15] S.K. Chaharsooghi and A.H. Meimand Kermani, "An effective ant colony optimization algorithm (ACO) for multi-objective resource allocation problem (MORAP)", *Applied Mathematics and Computation*, Vol. 200, No. 1, Jun 15, 2008.

[16] A. Ahuja, S. Das, and A. Pahwa. "An AIS-ACO Hybrid Approach for Multi-Objective Distribution System Reconfiguration", *IEEE Transactions on Power Systems,* Vol. 22, No. 3, August 2007.

[17] H. Bai, P. Zhang, V. Ajjarapu, "A novel parameter identification approach via hybrid learning for aggregate load modeling", *IEEE Transactions on Power Systems*, Vol. 24, No. 3, 2009.

[18] P. Maghouli, S. H. Hosseini, M.O. Buygi, M. Shahidehpour, "A multi-objective framework for transmission expansion planning in deregulated environments", *IEEE Transactions on Power Systems*, Vol.24, No.2, 2009.

[19] Y. Yare, G.K. Venayagamoorthy, U.O. Aliyu, "Optimal generator maintenance scheduling using a modified discrete PSO", *IET Generation, Transmission & Distribution*, Vol. 2, No. 6, Nov. 2008.

[20] A.H. Shahirinia, A. Hajizadeh, A.R. Moghaddamjoo, "Genetic-based size optimization of renewable energy sources", *International Journal of Power and Energy Systems*, Vol. 28, No. 3, 2008.

[21] A. Pregelj, M. Begovic, A. Rohatgi, "Recloser allocation for improved reliability of DG-enhanced distribution networks", *IEEE Transactions on Power Systems*, Vol. 21, No. 3, August 2006.

[22] J. Kennedy & R.C. Eberhart, "Particle Swarm Optimization," *Proceedings, 1995 IEEE Conference on Neural Networks*, Vol. 4, 1995.

[23] X. Hu, R. Eberhart, and Y. Shi. "Recent advances in particle swarm", Proceedings from IEEE Congress on Evolutionary Computation , 2004.

[24] Maurice Clerc, Particle Swarm Optimization, Wiley, 2008.

[25] B. Fox, W. Xiang, H.P. Lee, "Industrial applications of the ant colony optimization algorithm", International Journal of Advanced Manufacturing Technology, Vol. 31, No. 7-8, January 2007.

[26] C.M. Colson, M.H. Nehrir, & C. Wang, "Ant colony optimization for microgrid multi-objective power management", *Proceedings of the 2009 IEEE/PES Power Systems Conference and Exposition*, 2009.

[27] E. Carpaneto, "Distribution system minimum loss reconfiguration in the Hyper-Cube Ant Colony Optimization framework", *Electric Power Systems Research*, Vol. 78, No. 12, Dec. 2008.

[28] W. Tippachon & D. Rerkpreedapong, "Multiobjective optimal placement of switches and protective devices in electric power distribution systems using ant colony optimization", *Electric Power Systems Research*, Vol. 79, No. 7, July 2009.

[29] L. Wang & C. Singh, "Reliability-constrained optimum placement of reclosers and distributed generators in distribution networks using an ant colony system algorithm", *IEEE Transactions on Systems, Man and Cybernetics Part C (Applications & Review)*, Vol. 38, No. 6, Nov. 2008.

[30] Chung-Fu Chang, "Reconfiguration and capacitor placement for loss reduction of distribution systems by ant colony search algorithm", *IEEE Transactions on Power Systems*, Vol. 23, No. 4, Nov. 2008.