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ORIGINAL ARTICLE

Integrating renewables economic dispatch with demand side management in micro-grids: a genetic algorithm-based approach

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Abstract Economic dispatch and demand side management are two of the most important tools for efficient energy management in the grid. It is a casual observation that both these processes are intertwined and thus complement each other. Strategies aiming to optimize economic dispatch have implications for demand side management techniques and vice versa. In this paper, we present a genetic algorithm-based solution which combines economic dispatch and demand side management for residential loads in a micro-grid. Our system collects preferences of demand data from consumers and costs of energy of various sources. It then finds the optimal demand scheduling and energy generation mix for the given time window. Our evaluations show that the given approach can effectively reduce operating costs in a single- and multiple-facility micro-grids for both suppliers and consumers alike.

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Nomenclature

VC	Cut-in speed of wind generator
VR	Rated speed of wind generator
VF	Cutoff speed of wind generator
C	The set of consumers under the micro-grid
S	The set of currently available energy suppliers to the micro-grid
μ_x	Total energy demand by consumer x
$\mu_{x,h}$	Total energy demanded by consumer x at hour h
$\alpha_{y,h}$	Total energy available from supplier y at hour h
$\lambda_{y,h}$	Price of energy from supplier y at hour h
$\beta_{x,y,h}$	Total energy allocated to consumer x from supplier y at hour h

Introduction

Economic dispatch and demand side management (DSM) are two of the most important tools for efficient energy management in the grid. Whereas economic dispatch is the task of finding the right and optimal mix of energy for the given demand, demand side management aims at managing end user demand to reduce cost. There are various ways to achieve this goal, the most common way is by shifting movable loads to off-peak time or times of lower cost. The goal is to reduce energy cost by balancing energy resources against demand.

It is a casual observation that both these processes are interlinked. Economic dispatch tries to reduce cost according to available demand and DSM tries to manage demand to reduce cost. It stands to reason that if both tasks are considered together, where DSM and economic dispatch planning include their interdependent constraints, a better solution may emerge.

Specifically, in renewable solution implemented on a small scale by the consumers, this aspect becomes more evident. In these systems, typically, the excess low-cost energy from renewable sources is either stored in battery systems or sold back to energy retailers up the grid. These approaches miss the opportunity to take advantage of the localized aspects of micro-grids and incur significant costs associated with often expensive, inefficient energy storage systems and transmission losses upstream to the grid. By more immediately utilizing this excess energy, these losses are minimized and equal or lower energy costs can be achieved with potentially fewer distributed renewable resources, creating savings in the installation, maintenance, and operating costs associated with them.

In this paper, we present a strategy to integrate DSM and economic dispatch for renewables in a localized setting. In our strategy, user preferences and generation capacity are encoded as constraints of the system. With these constraints, an optimization objective function is constructed from the cost of generation for each unit for each hour. Afterwards, a genetic algorithm is used to find the optimal solution for the problem. Our results show that this integrated methodology is up to 15 % more cost-effective than state-of-the-art independent DSM and economic dispatch models for a neighborhood as compared to our combined DSM and economic dispatch implementation for an integrated neighborhood approach (Gudi et al. 2011).

Our study is focused on the abstraction of houses, renewable energy resources (RES), and devices and their average generation and consumption similar to the works of Shivakumar et al. (2013), Livengood and Larson (2009), Ranade and Beal (2010), and Conejo et al. (2010). Study of integration of power flows in the micro-grid and integration of different energy sources for a robust power delivery is the next step of deploying this system but is beyond the scope of the current work.

The remaining sections of the paper are organized as follows: In "Economic dispatch and DSM opportunities in smart grids," we discuss the opportunities for economic dispatch and DSM that have emerged through research in smart grids and micro-grids. In "Operational system," the operation system is discussed and in "Problem formulation," the problem present in this operational system is modeled and design objectives are discussed. In "Genetic algorithm," the genetic algorithm formulation and its algorithm is discussed. "Model implementation" specifies implementation details for the various steps for the genetic algorithm, and finally, in "Evaluations and results," evaluation of the numerical results and a summary of the findings are presented.

Economic dispatch and DSM opportunities in smart grids

There are two developments in recent times which have provided new opportunities for economic dispatch and DSM. On one hand, smart grid initiatives have provided greater surgical control of user-side power consumption (Coll-Mayor et al. 2007; Farhangi 2010; Ipakchi and Albuyeh 2009). This is being used as an opportunity by various researchers to define fine-grained DSM (Conejo et al. 2010; Gudi et al. 2011; Livengood and Larson 2009; Ranade and Beal 2010) as opposed to the blanket DSM employed in traditional grids (Amjady 2007; Gellings and Chamberlin 1993; Shahidehpour et al. 2002; Weron 2006). On the other hand, distributed generation and renewable sources have enabled the emergence of micro-grids within which more efficient and exact economic dispatches are possible (Jiayi et al. 2008; Lasseter et al. 2002; Tsikalakis and Hatziargyriou 2008; Yalcinoz et al. 2001).

Demand-side management programs in traditional grids usually involved manual control of end user devices (Gellings and Chamberlin 1993). Automation is proposed by some authors, but the control was blanket in the sense that the participating devices were either switched on or off (Albadi and El-Saadany 2007). There is no concept of intelligent planning for the operation of these devices.

Fine-grained DSM strategies, on the other hand, can perform complicated automated device scheduling based on consumer preferences and electricity prices. Furthermore, with the advent of more dynamic forms of pricing, they have become increasingly flexible in order to adjust for fluctuations in the cost of electricity. These DSM techniques usually manage energy within a single household and typically involve capitalizing on variable pricing by energy providers and integration of house-based renewables for cheaper energy utilization. Several papers have already been published which relate to such techniques. An example is the work presented by Livengood and Larson (2009) which uses a stochastic programming solution to optimize user-side demand. However, the approach focuses on optimizing for a single household at the granularity of individual consumer devices. On the other end of the spectrum is the probabilistic demand shaping and peak-shaving approach outlined by Ranade and Beal (2010) which concerns itself with reducing demand by multiple consumers during peak hours but does not focus on actual scheduling of activities.

Economic dispatch in the scope of micro-grids has also generated a fair amount of interest. The main contention here has been to incorporate renewables (Jiayi et al. 2008). While Celli and colleagues have proposed methods to use micro-grid economic dispatches to maximize benefit in integration with the rest of the grid, Tsikalakis suggests a system where intelligent controllers at consumer level collaborate with a micro-grid central controller (Tsikalakis and Hatziargyriou 2008). In this case, the central controller is responsible for dispatch whereas local controllers are responsible for DSM (Tsikalakis and Hatziargyriou 2008). In addition to these solutions, Lasseter and colleagues have also designed a framework for economic dispatch in micro-grids (Lasseter et al. 2002). A genetic algorithm-based approach by Yalcinoz and colleagues can also be found in the current literature (Yalcinoz et al. 2001). However, all of these systems cater to economic dispatch independent of DSM.

Recently, a series of researchers have developed economic dispatch solution incorporating the demand response saving. For instance, Behrangrad et al. presented an economic dispatch model which uses the demand response as spinning reserve (Behrangrad et al. 2011). Parvania and Firuzabad presented an economic dispatch model which used the demand response planners (DRPs) as an integral part of grid and modeled the saving realized by DRPs in planning optimal economic dispatch (Parvania and Fotuhi-Firuzabad 2010). However, in both the instances, economic dispatch does not actually plan household consumption in the same way as Conejo et al. (2010), Livengood and Larson (2009), or Ranade and Beal (2010) do.

As demonstrated later in our experiments, treating DSM and economic dispatch as independent modules can result in suboptimal power pricing across the grid. Instead, in this paper, we combine fine-grained DSM with economic dispatch of micro-grids and attempt to find an optimal schedule for both under a single optimization model. This way we are able to leverage the power of DSM to arrive at better power dispatches, resulting in a lower cost than independent DSM and economic dispatch systems.

We specifically consider the micro-grid developed within the EU R&D MG project and presented by Jiayi et al. in their survey (Jiayi et al. 2008). In this micro-grid is a hierarchical structure where a micro-grid controller (MGCC) acts as a broker between load controllers (LC) and micro-sources (MS). In the survey, it has been shown that LC and MS are two independent entities and optimize their operations independently. We show that a combined model at MGCC level, at least for the renewable MS, provides a better optimization than independent LC and MS planning.

This is under the assumption that micro-grid implements an economic operational cycle similar to that in the work of Dimeas and Hatziargyriou (2005). In this setup, MGCC announces the beginning of market period and MS and LC predict their production and demand, respectively, and bid for the resources under MGCC. MGCC then resolves the market using some algorithm. When we consider DSM within this setup, we see a point of combined optimization for MS and LC.

To our knowledge, such solutions for micro-grids are rare. Approaches that attempt to bring together both sides of this relationship are limited in their scope. For example, the linear programming optimization solution utilized by Conejo and colleagues is only applicable to a single-load, single-supplier scenario (Conejo et al. 2010). Similarly, the particle swarm optimization of Wang and colleagues handles multiple sources but is designed to function on the scale of single-facility micro-grids only (Gudi et al. 2011). A need exists for a more holistic approach that can encompass both these aspects of energy management while accommodating multiplicity of suppliers and consumers.

In this paper, we satisfy this need by presenting a genetic algorithm-based solution for combined power dispatch and DSM for residential users in a micro-grid. Our proposed strategy has a bottom–up approach where individual consumers in the micro-grid communicate their power requirements as a set of constraints over a neighborhood area network to the local micro-grid. The energy management system (EMS) of the micro-grid then collates this information and uses it in conjunction with information from available power supplies to generate an optimum power distribution schedule. This schedule satisfies the maximum number of consumer constraints at the lowest possible total cost to all the consumers. It is important to note that while this algorithm can be applied on an individual consumer level, the primary focus is to optimize across multiple small-scale consumers located within a single micro-grid.

An important question within the scope of renewable integration is their intermittency. It has already been established that integration of MS in micro-grid and for RES requires an intermediate storage. However, the sizing of battery is problematic and adds cost to the system. In this paper, we assume that a storage of sufficient size is available to mitigate the response time of MS and intermittency of RES. However, unlike other DR systems (Gudi et al. 2011; Livengood and Larson 2009), we do not consider this storage as an active source in our planning. The storage is placed as a backup measure to safeguard against failures. Using this storage for any purpose can place our system in a compromised state which we would like to avoid under any circumstance. Furthermore, for our optimization, we only consider the hourly average wind speed and solar irradiance. This, in conjunction with the storage, provides us with sufficient buffer to plan DR. This treatment of renewable is consistent with similar works in the literature (Gudi et al. 2011; Livengood and Larson 2009).

To test the feasibility of our approach versus existing solutions, we have benchmarked it on two levels. At the first level, we construct a power dispatch and DSM system for a single house and compare it with a state-of-the-art energy management system (Gudi et al. 2011) at the same scale. Our results show that our genetic algorithm-based solution is up to 10 % more effective. We then extrapolate to multiple houses that would be present in a micro-grid and show that our technique is able to utilize the combination of DSM and economic dispatch to deliver higher savings than DSM and economic dispatch systems working independently. In this way, our contribution is unique that it brings the best of these two strategies together and forms a succinct solution for energy management at the level of a micro-grid.

Operational system

In this section, we discuss the operational system for which our technique is designed. Our proposed strategy is for a micro-grid setup with variety of micro-generation and renewable energy resources. Houses have some home area network or smart devices setup which can monitor and control energy consumption.

The planning module operates on a 24-h planning horizon for its scheduling. It is assumed that pricing and availability details of energy supplies are known 24 h in advance due to day-ahead pricing. It is also assumed that consumption schedules for the consumers are available. These schedules are in the form of demand of energy in each hour and the elasticity bounds for movable loads.

The proposed algorithm can readily be implemented in the EMS of any micro-grid network. Moreover, it possesses the required speed and scalability to enable its practical use in such a case, as demonstrated later in the paper with the help of experiments.

Problem formulation

The objective of this approach is to determine an effective distribution of sources of energy between the multiple consumers in a micro-grid such that the total cost across all consumers is minimized and all consumer-specified and design constraints are satisfied. Specifically, we consider a daily 24-h time window and must generate a mapping of consumers to suppliers at the resolution of hourly intervals for certain amounts of power.

The objective function selected for be minimized is defined below:

$$\sum_{x\in C}\sum_{y\in S}\sum_{h=1}^{24}\lambda_{y,h}\times\beta_{x,y,h} \tag{1}$$

Subject to:

$$\sum_{x\in C}\sum_{y\in S}\sum_{h=1}^{24}\beta_{x,y,h}=\sum_{x\in C}\mu_x \tag{2}$$

$$\sum_{y\in S}\sum_{h=1}^{24}\text{boole}\left(\alpha_{y,h}<\sum_{x\in C}\beta_{x,y,h}\right)=0 \tag{3}$$

$$\sum_{x\in C}\sum_{h=1}^{24}\text{boole}\left(\mu_{x,h}>\sum_{y\in S}\beta_{x,y,h}\right)=0 \tag{4}$$

Constraints in Eqs. 2 and 3 define the operational limits of the intended system, which should be satisfied throughout system operation for any feasible solution. Constraint in Eq. 2 stipulates that the load assigned to different houses should be equal to the total system demand. This does not limit generation but limits the assignment of that generation to demands. Constraint in Eq. 3 stipulate that for each hour and for each generation unit, the energy dispatch from that unit should be less than or equal to its projected generation. Each of these <supplier,hour> tuples is evaluated as a Boolean. The sum of the contrapositive of the previous statement is used as the constraint. That is, we evaluate that generation is lesser than dispatch. The constraint is that for all the <supplier,hour> tuple, this statement should be false. This contrapositive is helpful in making a generic statement since otherwise the right-hand side of the equation will be equal to the number of suppliers × hours in planning window. These two equations in combination ensure that the energy supplied does not surpass energy demand and does not exceed what suppliers can provide in given intervals, respectively. Solutions that violate these constraints cannot be considered valid.

Constraint in Eq. 4 defines the consumer-specified constraints which individual consumers over the micro-grid communicate to the micro-grid EMS. These constraints help ensure that any solution meets consumer requirements by allowing consumers to specify how much power they need within a certain time interval. The time interval can be rigid (consumer 5 must receive 5,000 kWh between 3:00 p.m. and 4:00 p.m.) or flexible to allow for cost savings via scheduling (consumer 6 must receive 10,000 kWh through any 2 h between 12:00 a.m. and 5:00 a.m. in chunks of 5,000 kWh). Solutions that violate only Eq. 2 can theoretically be considered valid—subject to a penalty function as described by Michalewicz (1995) that penalizes based on how many constraints were violated and by what margin—but for the purposes of this work, we attempt to ensure that every consumer constraint is satisfied if supply allows for it—which, in many ways, is a harder problem. Consumers must be motivated to opt into DSM schemes and fulfilling their requirements as far as possible plays an essential role in this function.

Genetic algorithm

Genetic algorithms are a particular class of evolutionary algorithms that are based on evolutionary processes, such as reproduction, crossover, and mutation. An initial population of strings (**chromosomes**), which encode possible solutions (**phenotypes**) to an optimization problem, evolves toward better solutions. The evolution starts from a population of randomly generated chromosomes and happens across a prespecified number of generations. For every generation, the fitness of all chromosomes in the population is calculated using the objective function. Multiple chromosomes are stochastically selected from the current population (based on fitness to some degree) to form the **gene-pool** for the next population. The next population is populated using a combination of the very best solutions from the previous generation (**elitism**) and modified chromosomes from the gene pool (**cross-over** and possibly randomly **mutated**). The new population is then used in the next iteration of the algorithm. In this way, fitter solutions have a higher probability of being reproduced in the next generation and mutation and crossover help avoid falling into the trap of local minima of results by ensuring that the chromosomes do not become too similar.

The computational procedure used in the approach is laid out as follows:

Algorithm 1 DSM–economic dispatch planner

Step 1: Input supplier, consumer, and consumer constraint tuples and specify generation shift factors: population size, number of generations, mutation probability, elitism percentage, and tournament size.
Step 2: Pseudo-randomly generate the initial population.
Step 3: Rank chromosomes using the fitness function described in Weron (2006).
Step 4: Apply elitism by reserving slots in the next generation for the highest scoring chromosomes of the current generation.
Step 5: Build gene pool for the next generation by the Tournament Selection scheme.
Step 6: Apply Crossover and Mutation operators on gene pool members to repopulate the next generation.
Step 7: Repeat steps 3–6 until some terminating generation number is reached or time limit is exceeded.
Step 8: Output the fittest chromosome as the proposed optimum solution.

Model implementation

In this section, we will discuss the details of each step of our genetic algorithm implementation. We will discuss steps 1 to 6 since steps 7 and 8 are trivial.

Input representation

Generation shift factors are specified as simple real number values. Supplier information is modeled as a 3-tuple which holds the supplier identifier, energy retail price, and a list of how much kilowatts of energy is available for each hour of the 24-h window in question. Consumer information is modeled as a simple 2-tuple that contains the consumer identifier and total energy required. Similarly, consumer constraints are modeled as a 5-tuple holding a consumer identifier representing whom the constraint applies to, the amount of energy to be delivered, and the range of hours it must be delivered in. The fifth field denotes the basic quantity of energy the algorithm should allocate when handling the constraint. It makes no sense to allocate 9 kWh in 1 h and 1 kWh in the next if the constraint was built to model the functioning of a pair of appliances that required 5 kWh each and could be scheduled in separate hours or together. Specifying 5 in this field would ensure that only useful allocations are made.

Phenotype representation

A fundamental aspect of genetic algorithms (GAs) is the encoding of solutions appearing in the population. This encoding, along with the associated decoding to return to the natural problem space, is essential to the GA operations. Each phenotype consists of a set of elements called **genes** that are 4-tuples holding the consumer identifier, the supplier identifier, the energy allocated, and the hour in question (1–24). When encoded as a chromosome, each of these fields is represented as a real number. While binary encoding is traditionally the most common method, we have utilized the real-valued representation scheme for the benefits it offers in numerical function optimization (Gomez-Villalva and Ramos 2003;

Philpott and Pettersen 2006). Using real-number encoding increases the efficiency of the GA since conversion of the chromosomes to binary is no longer needed, avoids loss in precision due to discretization to binary, requires less memory as it relies on the computer's internal floating-point architecture, and offers the choice to use a greater variety of genetic operators (Borenstein 2005).

Generating the initial population

One open problem faced by evolutionary algorithms that handle constraints for numerical optimization problems such as this one is that of building an initial population of chromosomes that is actually feasible at all. When the fitness function is complex and noncontinuous in combination with a search space that is relatively large, GAs can struggle. This is the case here where a solution must always fulfill Eqs. 2 and 3 to be valid at all and must fulfill Eq. 4 in order to maintain the quality of service threshold at acceptable levels for consumers. The cardinality of these consumer-specified constraints can reach over 200 for a relatively large micro-grid. Every consumer has fixed but different minimum consumption for every hour of the day along with variable energy requirements that lie within specific time intervals. Generating even a single solution randomly that is capable of satisfying each of these constraints can be time-prohibitive.

To overcome this challenge, our approach uses a pseudo-random technique that ensures user-specified constraints are satisfied while generating an initial population of size N:

Algorithm 2 Population generation

Step 1: Select the first constraint from the list of user-specified constraints.

Step 2: Randomly select an hour from within the time range given in the constraint.

Step 3: Pick a supplier by filtering for the set of suppliers that are selling energy at that hour and randomly selecting one of them.

Step 4: Determine how much power to allocate by randomly picking a multiple of the basic quantity of energy defined in the constraint (See section A) up to the total energy required. However, if the basic quantity exceeds the total energy required, randomly pick a value from 1 up to the total energy required.

Step 5: Consider the selected hour, supplier, and power to allocate—along with the consumer identifier from the constraint—as a gene and append it to the chromosome.

Step 6: If the total energy required by the constraint has not been satisfied, update this quantity by subtracting the power allocated in step 4 and repeat from step 2.

Step 7: Pick the next constraint and repeat from step 2 until all constraints have been satisfied.

This ensures that any generated solution satisfies Eqs. 2 and 4. Additional energy required by the consumer that was not covered by any constraint is then handled by generating genes repeatedly through a completely random procedure until all requirements have been met. Solutions generated in this fashion can still violate Eq. 3 since overallocation on a particular supplier can occur so checks should be evaluating the fitness of a solution.

Elitism

A fraction of the fittest chromosomes N_e are guaranteed a place in the next generation directly without any mutation or crossover operators applied. This helps ensure that if an optimum chromosome is found, it remains a competitive candidate. Note that these elitist chromosomes in the original population are also eligible for selection and subsequent recombination in the gene pool.

Selection scheme

After elitism has been applied, a subset of the N chromosomes is selected to be used as parents for the succeeding generation. It is essential that priority is not monopolized by chromosomes with the highest fitness values since this tends to reduce the diversity, often causing premature convergence in a local optimum. To avoid this, our approach uses tournament selection. Chromosomes are inducted into $(N - N_e)$ "tournaments" by random sampling (with replacement) from the original population. The winner of each of these tournaments (the one with the best fitness) is placed in the gene pool as a parent for the next generation of chromosomes. Stronger chromosomes can enter the pool multiple times, but by keeping the tournament size small, weaker chromosomes have a reasonable chance to be selected as well (Holland and Mansur 2006).

Reproduction scheme

The $(N - N_e)$ parent chromosome entries from the gene pool are paired together to help breed the $(N - N_e)$ new chromosomes needed to repopulate the next generation. Pairs are subjected to a crossover operator with a prespecified probability which produces two offspring. If the crossover operator is not applied, the offspring will be direct clones of the parents. Since a given population might not contain enough diversity to find the solution via crossover operations alone, the algorithm also uses a mutation operator on any given offspring with a prespecified probability in an attempt to generate novel solutions. Details on these two operators are given below:

1. Crossover operator: If crossover does take place, then the two offspring are produced according to an interchange of parts of the chromosome structure of the two parents. We accomplish this by one-point crossover, where the numbers appearing after a randomly chosen dividing (splice) point in the genes of the two chromosomes are interchanged.
2. Mutation operator: For a chromosome subject to mutation, we take a randomly chosen subset of its genes. For each of these genes, mutation is accomplished by adding a small independent normal to the hour at which power was to be supplied and switching the supplier identifier to another randomly selected valid value.

Evaluations and results

Experimental setup

In this section, we describe the set of experiments designed to evaluate the feasibility of our approach. Figure 1 shows the flow of data in the system. There are two input providers to the system. The suppliers provide their day-ahead approximate availability and costs. The consumer's smart home system provides the planner with consumption constraints according to user's preferences. The GA optimizer keeping the constraints and cost in view creates a consumption schedule for

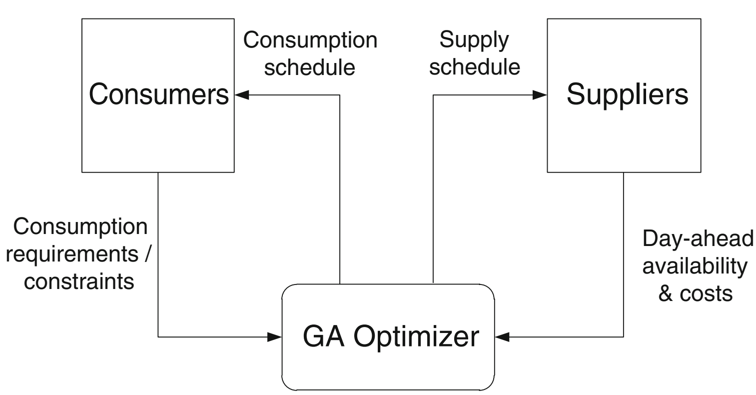

Fig. 1 Flow of data in economic dispatch–DSM system. The suppliers will provide their day-ahead approximate availability and costs. The consumer smart home system will provide the system with consumption constraints. The genetic algorithm will in return provide a plan to households to consume energy and will provide plans to generators for optimal dispatch

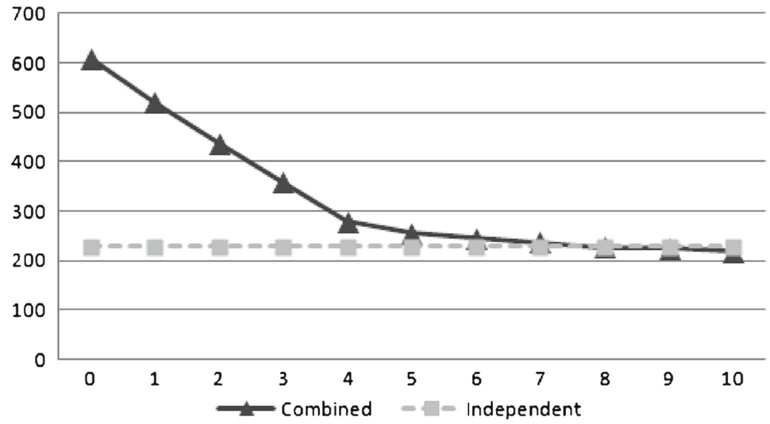

Fig. 2 Unit commit for renewables: *Solid line with triangle markers* represents the daily cost of power when *X* sets or renewables are installed in combined configuration. *Dashed line* represents the cost of 10 renewables in distributed controller configuration

the consumers and a dispatch schedule for the generating units (Fig. 2).

The GA optimization engine is set up with the following parameters: We set up our genetic algorithm with a population size of 1,000 across 100 generations with a tournament size of 3, and elitism, mutation, and crossover probabilities were set at 0.02, 0.05, and 0.5, respectively. The choice of these parameters was guided by Gomez-Villalva and Ramos (2003).

The daily cost rates for consumption of electricity used in both experiments are part of a cost rate structure plan obtained from Gudi et al. (2011) and shown in Table 1.

For renewable sources of energy, we utilize the wind turbines and photovoltaic cell. The specifications for these sources were also acquired from Gudi et al. (2011) and set as follows:

Photovoltaic cell:	Area 20 m^2
	Efficiency 12.5 %
Wind turbine:	Rotor diameter 4.75 m
	VC 2 m/s
	VR 8 m/s
	VF 25 m/s
	Turbine efficiency 35 %

Table 1 Energy rates for experiment (Gudi et al. 2011)

Time	Cost (cents/kWh)
7 a.m. to 9 a.m.	0.45
9 a.m. to 4 p.m.	0.30
4 p.m. to 6 p.m.	0.37
6 p.m. to 10 p.m.	0.45
10 p.m. to 7 a.m.	0.30

The wind speed and solar radiation data utilized during evaluations are delineated in Tables 2 and 3. This information was obtained from Lasseter and Paigi (2004) and Zareipour et al. (2004), respectively, and mirrors the values used in the case study outlined by Gudi et al. (2011). All the experiments were run on a commodity computer with core i5 processor and 8 GB of memory.

Experiment 1: single-house distributed configuration benchmarking

To evaluate the feasibility of our approach versus existing solutions, we benchmarked our GA against the state-of-the-art energy management solution presented in the study by Gudi et al. (2011).

The case study therein incorporates distributed renewable resources and utilizes detailed consumption information of sample household appliances to output a consumption schedule that minimizes total cost to the micro-grid. The properties (number of appliances, time of operation, power consumption, and priority) of the appliances were set as shown in Table 4. It should be noted that appliances with multiple-duty-cycle operation have variation in their peak power consumption. The goal of the DSM is to reduce the cost of energy and is constrained by the practical consideration that all the operations for the devices must be completed within the planning window. The selection of device is according to the priorities set by the user. This is the experimental setup

Table 2 Solar insolation values

Hour of day	1	2	3	4	5	6	7	8
Insolation (W/m^2)	0	0	0	0	0	0	56	214
Production (W)	0	0	0	0	0	0	1.4	5
Hour of day	9	10	11	12	13	14	15	16
Insolation (W/m^2)	346	703	955	1,044	989	949	899	789
Production (W)	9	18	23	26	25	27	22	20
Hour of day	17	18	19	20	21	22	23	24
Insolation (W/m^2)	581	352	73	0	0	0	0	0
Production (W)	15	8	2	0	0	0	0	0

of Gudi and colleagues and is consistent with the experimental setup designed by Livengood and Larson (2009) and Ranade and Beal (2010). We see possible improvements in this scheme; however, we would first like to present comparison with the existing work to benchmark our results.

Based on the cost rate plan defined in Table 1, the results for optimal DSM planning using Gudi et al. (2011) and our genetic algorithm implementation are shown in Table 5. There are three results for comparison. First is the base system without DSM, and the second is when DSM is applied but without any renewable resources. The third result is the savings of application of DSM using renewable sources. The percent cost savings for direct operation with renewable resource integration is 10.39 %.

Results

The results for operation with renewable resources are competitive but not immediately comparable directly since our results do not account for the use of a 100 % efficient energy storage system that begins with 40 % state of charge at the onset of simulations in the study by Vittal (2010). We opt out of using such energy storage systems in active DSM planning in favor of sharing excess energy production from on-site renewable sources across multiple consumer loads in the micro-grid as will be shown in experiment 2. In this way, we maximize the use of these resources during off-peak hours and create savings by overcoming energy losses to storage inefficiencies and minimizing the installation and operational costs associated with batteries and energy transformations.

Experiment 2: distributed controller configuration versus combined controller configuration

Having established the feasibility of our algorithm with respect to alternate solutions at a single-consumer level, we extended the scale to simulate a multiple-facility micro-grid. For this, we used energy consumption data collected from 10 houses (Table 6). Due to privacy requirements, we added a small amount of random noise in the data while making sure that the characteristics of the data are not affected. Our comparison is between a DSM in a distributed controller configuration where each house has its own DSM planner against a DSM where loads of each house are combined into a single system. This single system acts as the planner combining the energy produced and the devices available for scheduling. The goal is to maximize the renewable energy usage across the

Table 3 Hourly average wind speeds

Hour of day	1	2	3	4	5	6	7	8
Wind speed (kmph)	45.2	16.8	5.9	34.4	20.7	27.2	36.8	12.2
Production (W)	0	831.25	325.53	0	831.25	0	0	831.25
Hour of day	9	10	11	12	13	14	15	16
Wind speed (kmph)	6.5	37.6	3	31.6	19.7	44.2	11.3	11.4
Production (W)	439.74	0	31.33	0	831.25	0	831.25	831.25
Hour of day	17	18	19	20	21	22	23	24
Wind speed (kmph)	13.7	27.6	34.9	20.9	31.1	3.24	35.1	2
Production (W)	831.25	0	0	831.25	0	42.90	0	0

Table 4 Usage consumption pattern of the user

Appliance name	Time of operation	Time of operation without DSM	No. of appliances	Consumption (W)	Priority
				3,500	
Air conditioner	Full day	Full day	3	2,500	2
				1,500	
Clothes dryer	120 min	9 p.m.–11 p.m.	1	650	6
Dishwasher	180 min	9 a.m.–10 a.m.		1,200	4
		9 p.m.–11 p.m.	1	1,200	
				800	
Refrigerator	Full day	Full day	2	600	1
				450	
Pool pump	240 min	4 p.m.–8 p.m.	1	2,000	7
Washing machine	60 min	8 p.m.–9 p.m.	1	800	5
		6 a.m.–11 a.m.		700	
Water heater	Full day*	11 a.m.–6 p.m.	1	500	3
		6 p.m.–1 a.m.		700	

Table 5 Experimental results: without DSM is the base system running without any renewables and without applying any DSM

Scenario	Cost (cents/day)	
	Benchmark	Experiment
Without DSM	131	–
With DSM	88.7	80.35
With DSM & renewable sources	22.5–26.9	23.47

With DSM is a system with a DSM but no renewable. With DSM and renewable is when houses are fitted with renewable sources of energy, a DSM is applied to manage the energy loads

micro-grid and avoid storage or inefficient back selling.

To conduct this experiment, we executed our algorithm for each of the houses individually and added the values to obtain the total cost for the neighborhood. Table 7 lists the cost of power in cents per day for each house while each house uses the DSM strategy of experiment 1. Each house possesses its own wind turbine and photovoltaic cell. The specifications for these were the same as those used in experiment 1. We use this result as the benchmark and compare it against our combined configuration model.

In the combined model, as compared to the previous one, the houses could share excess energy from their renewable resources with each other. In this way, we leverage the combined energy production and larger device management domain to

Table 6 Independent run DSM results

House no.	Cost (cents/day)
1	20.49966
2	34.80037
3	10.4551
4	20.64298
5	21.05456
6	13.89449
7	39.52733
8	25.22495
9	29.82267
10	12.23465
Total	228.15676

Table 7 Combined DSM results

Renewable sets	Cost (cents/day)
1	519.9168
2	438.0797
3	358.3161
4	278.9873
5	254.5108
6	245.005
7	237.1987
8	227.0373
9	224.8754
10	217.5591

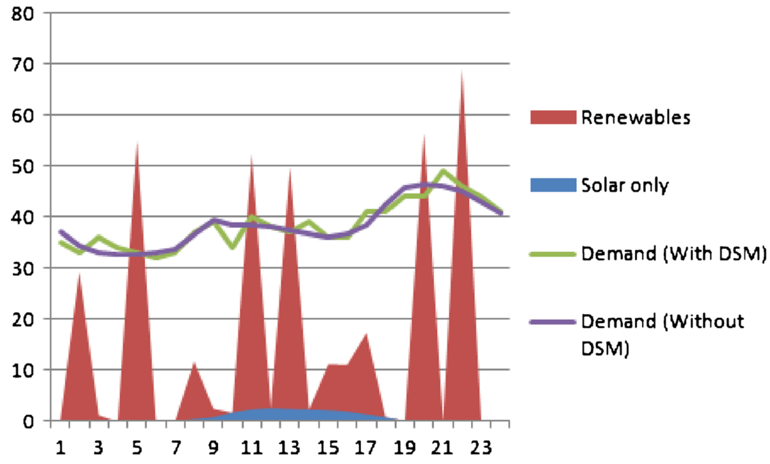

Fig. 3 Total demand for 10 houses and availability of renewable over the 24-h period

increase system efficiency. As an illustration of the outcome, Fig. 3 shows the total demand for 10 houses and the generation through wind and solar panels.

Results

Our first result compares the total energy cost for both configurations. Whereas our total cost with distributed controllers was 228.16 cents per day, the cost using combined configuration came out to 217.6. This is a 10.56 cents or 5 % of savings by using exactly the same devices but a different controller methodology.

Discussion on unit commit problem

As a side note, we further investigated if we can solve the unit commit problem with this setup. We started with no renewables and calculated a plan by adding one set of renewables in each iteration. Figure 2 shows a graph of this gradual increase of renewables in combined configuration against the total cost of distributed controller configuration. We consider 10 sets of renewables in distributed controller configuration since combining power of more than one renewable set is not possible in distributed configuration. We see that for the same demand pattern, seven renewable pairs will be sufficient to provide energy at the same energy cost as compared to each house having its own renewables and controllers. This means that we can save as much at 30 % of setup cost or save 5 % of operational expenses through a combined configuration controller.

Conclusion and future work

This paper provides a genetic algorithm to be integrated into the EMS of a multi-facility micro-grid. The algorithm offers a scalable means of minimizing energy costs to the micro-grid's consumers while meeting their time-based requirements. Simultaneously, it assists energy suppliers by determining the optimum configuration of generational facilities that must be deployed to meet the stipulated demand. The interaction takes place on a daily basis where energy consumption, user-specified constraints, and supplier day-ahead pricing information is. A pair of case studies demonstrates the feasibility and effectiveness of the proposed algorithm to minimize total cost to both the suppliers and consumers within a micro-grid that integrates the proposed procedure in its EMS.

There are many areas in which the algorithm might be further improved. Constraint-capturing mechanisms are one obvious place: where integration with negotiation algorithms that bridge the gap between algorithms that operate on the individual consumer level such as those of the study by Livengood and Larson (2009) and the larger multi-facility micro-grid level would make the overall system more dynamic in the face of changing consumer behavior. Similarly, ensuring fairness to individual consumers could be handled in a more sophisticated process using a tiered-pricing schema from individual suppliers after distributing less-expensive energy resources evenly. More lenient penalty functions for not meeting user-specified constraints are possible as well—with users being better able to prioritize cost-cutting measures over device usage and vice versa. Finally, an obvious next step is to deploy the algorithm on a small multi-facility micro-grid, validating that it behaves as expected in a real network environment before moving toward test deployments with actual consumers.

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