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A Memory-Based Genetic Algorithm for Optimization of Power Generation in a Microgrid

Mohd Mussa[1], Parwinder Singh[2,*], Kamaljeet Singh[2]

Abstract

Due to advancement in power electronics field, it is becoming more feasible to integrate renewable energy into power grid. Renewable energy sources are prompting more and more small investors to invest in generation and distribution of renewable energy at microgrid level. The increased competition requires energy producers to offer energy at minimum possible cost to gain the confidence of consumers, which needs efficient methods to schedule energy generation among the available renewable energy sources. To reduce the cost of power generation, the Energy Management System (EMS) uses optimal hourly scheduling of power generation. In a power grid system consisting of renewable energy source, we use energy management system which should gather all the needed information, solve an optimization problem, and communicate the correct allocation of energy back to each distributed energy resource (DER). The main objective of this project is to find optimal power scheduling at each hour with minimum cost among a number of DERs by using the memory-based genetic algorithm. It shares optimally the power generation in a microgrid. Generally, a microgrid consist of wind plants, photovoltaic plants, and a combined heat and power system. Let us consider two cases for optimization of power generation. In the first case we take five renewable generators and one conventional generator, and renewable generators are considered dispatchable. In the second case, two renewable and four conventional generators are considered, and renewable generators are considered non-dispatchable. Finally, to evaluate performance of our designed grid system we will compare both the case with existing literature methods.

Keywords: Microgrid, renewable energy sources, distributed energy resources, economic dispatch, energy management system, optimization, genetic algorithm, memory-based genetic algorithm, power scheduling, cost minimization, dispatchable generators, non-dispatchable generators

INTRODUCTION

Because of the growing need for electricity, the dwindling supply of fossil fuels, and the growing worry about global warming, we need to use as much energy as possible from renewable energy (RE) sources to make electricity. Sudden advances in the power electronics sector have made this trend even stronger. These advances make it possible to fully regulate sources.

The idea of a microgrid (MG) has come about because of the use of RE sources in the electric power system. A microgrid is a group of loads and micro sources that may be controlled as a single unit to provide both power and heat. Microgrids use renewable energy sources, called distributed generators (DGs), energy storage systems (ESS), and flexible loads. They are also located closer to the load centers [1].

Microgrids (MGs) are expected to provide customers with more efficient and environmentally

***Author for Correspondence**
Parwinder Singh
E-mail: parwindersingh4848@gmail.com

[1]Post Graduate Student, Department of Electrical Engineering, I.K. Gujral Punjab Technical University, Jalandhar, Punjab, India
[2]Assistant Professor, Department of Electrical Engineering, I.K. Gujral Punjab Technical University, Jalandhar, Punjab, India

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friendly energy than traditional power plants because distributed generators (DGs) are close to loads and renewable energy (RE) sources are included. They will also have less power loss and network congestion, and better power quality and reliability. Microgrids are likely to be a key part of smart grids in the electric power system in the future. Solar and wind are two renewable energy sources that are growing quickly. Solar is becoming more popular because its costs have dropped a lot in the past few years. Due to their intermittent, uncontrolled, stochastic, and highly variable nature, the integration of such sources into the electric power grid presents obstacles to its efficient operation, particularly at elevated penetration levels. For instance, load mismatches, inadequate load following, voltage instability, frequency deviation, substandard power quality, and reliability issues are some of the adverse effects that renewable energy sources present on the electric power network [2–7].

Microgrid can operate in two modes, first is grid connected mode and second is islanded mode. Grid-connected mode of operation of a microgrid aids in reducing the network losses and provides efficient load sharing; on the other hand, islanded mode of operation maintains the availability of supply, which increases its reliability during utility outages. Some of the advantages of incorporating a microgrid into the system are improvement in energy efficiency, voltage profile, reliability, and security of supply.

In this context, microgrids involve both ac and dc components. These components can be operated based on the principles of ac power systems or dc power systems or a combination of both through different architectures. MG architectures are mainly determined by the nature of the loads, the existing and planned distributed generators, the difficulties to build new electrical lines, the existing communications, the space to place energy storage devices and their specific power and energy requirements, among others. According to components, MG architecture can be divided into three different categories as followed:

- Ac microgrid,
- Dc microgrid, and
- Hybrid ac-dc microgrid.

LITERATURE REVIEW

Guan *et al*, in their paper "*Energy efficient buildings facilitated by microgrid*" had worked upon the smart microgrid idea [1]. Stochastic optimization can help you get the best building costs for electricity and natural gas. We use the AIMD linear programming method to figure out how to use the microgrid's renewable energy sources. There are several alternative ways to schedule renewable energy on a centralized mixed integer linear microgrid. Dolphin Echolocation Optimization is working on the plans for the microgrid renewable energy project. The size of a microgrid energy storage device is improved via a new version of the bat algorithm. Artificial fish swarms, which are spread out among multiple energy sources, make it easier to plan when power will be generated on microgrids [8]. Researchers looked at a lot of different ways to adjust the sizes of hybrid renewable energy systems. To deal with economic dispatch (ED), the fuel costs of the microgrid's dispatchable distributed generators (DGs) have been optimized while still staying within the restrictions of the operational environment. Mixed integer linear programming is used in demand response programming to find the best size for microgrid parts improvements made to HOMER and GAMS, which is the CPLEX solver [9]. We used the multi-objective particle swarm optimization (MOPSO) method to find the best system structure and component sizes for a Swedish off-grid hybrid microgrid system [10]. There are many different methods to talk about how to schedule power on microgrids. Suggesting a new way to schedule power that lets a microgrid's distributed economic dispatch work while also containing a lot of renewable energy and demand-side management (Figure 1). Using this method lowers the costs of distributed generation, distributed storage, dispatchable load utility, and worst-case transaction charges. First, we look into the potential DER availability, and then put into place stochastic microgrid energy scheduling.

DESS and RES will build a microgrid that is safe, cheap, and uses energy efficiently. Power management depends heavily on charging and draining DESS.

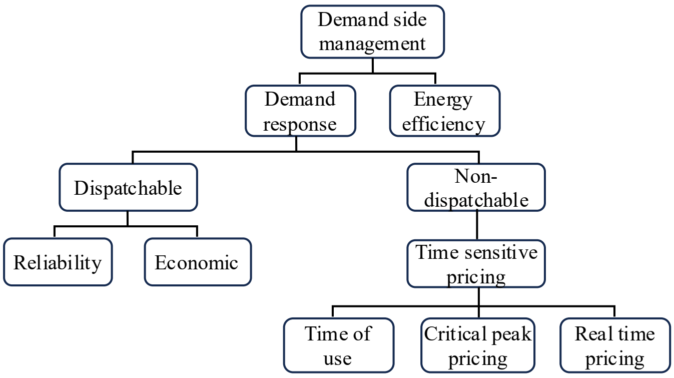

Figure 1. Classification of demand-side management techniques.

If the charging and discharging of DESS is not coordinated, it can cause power losses, malfunctions, voltage shifts, and other problems with power quality. Many different ways have been tried to solve the power scheduling problem, but no one has yet tried to optimize it. Smart grids improve situational awareness and let you quickly adjust how electricity is made. Because of this, the EMS will have trouble with communication and control. Many different ways have been tried to handle the problem of power scheduling, but no one has yet tried to optimize it. The main idea behind this study is that meta-heuristic optimization can be used to autonomously and optimally allocate power-generating jobs among microgrid distributed energy resources.

PROBLEM FORMULATION

Assumptions

The problem of scheduling is formulated under following assumptions:

- The requested electricity is less than the power that the available DERs in the microgrid can provide.
- Microgrid is running in islanded mode.
- We looked at the performance of the proposed solution by using a microgrid with three wind turbines, two PV plants, and one CHP.

Generation Cost

To allocate power demand among the accessible DERs, the EMS uses a variety of techniques in practice. Our aim is to find a way to distribute power that minimizes the total cost of producing the necessary amount of power. In response to this, we establish the following correlations between each DER and a quadratic cost function, a popular cost function in microgrid research, to solve this problem:

$$C_i(P_i) = a_i \times P_i^2 + b_i \times P_i + c_i \tag{1}$$

Pi is the quantity of power that the i_{th} DER makes in MW. a, b, and c are cost coefficients in the proper measurement unit that depend on the technology of the power plant (for example, fuel cost, efficiency, etc.). In particular, b comprises expenditures for operating and maintaining (O&M), fuel, and carbon, which are commonly shown in $/MWh. c is the cost in Currency Unit (CU) per hour, and i is the ith DER. The coefficient c takes into consideration the costs that occurs no matter how much energy is made. The quadratic Eq. (1) shows the whole cost of making any kind of unit, but people usually just look at the direct expenses and leave out the quadratic factor a, which makes optimization issues non-linear. Ignoring a is a popular approach to get rid of the non-linearity. But for this project, we employ the complete quadratic function to do the math. Table 1 gives a short overview of the cost coefficient functions' parameters that were taken from the study by Amrollahi and Bathaee [9].

Objective Function and Constraints

To lower the cost of generating power, an objective function (OF) is built from a quadratic cost function for each Distributed Energy Resource.

Table 1. Microgrid DERs cost coefficients.

Plant	a	b	c
PV plant 1	0.0055	29.30	4.45
PV plant 2	0.0055	29.58	4.46
CHP	0.0083	75.73	5.21
Wind plant 1	0.0027	17.83	4.6
Wind plant 2	0.0028	17.54	4.45
Wind plant 3	0.0026	17.23	4.44

The costs of producing electricity in a microgrid are the sum of the costs of each Distributed electricity Resource's generation. To satisfy the EMS balance notice, generated power must match the requested power. The equality requirement in Eq. (2) does this. Each hour's optimization challenge must be solved to fix scheduling.

$$\min OF = \sum_{i=1}^{N_{DER}} C_i\,(P_i) = \sum_{i=1}^{N_{DER}} a_i \times P_i^2 + b_i \times P_i + c_i$$

$$\text{Subject to } \sum_{i=1}^{N_{DER}} P_i = P_d \tag{2}$$

Where P_d is the demanded power.

In optimization theory, managing equality constraints is a significant challenge. A prevalent method to address this issue is the utilization of a penalty function. The penalty function changes an optimization problem with equality constraints into one without them, keeping the same number of choice variables as the original problem. The problem defined by Eq. (2) is revised through the application of the penalty function notion as follows:

$$\min OF = \left[\sum_{i=1}^{N_{DER}} a_i \times P_i^2 + b_i \times P_i + c_i\right] + P_f \times abs\left(\sum_{i=1}^{N_{DER}} P_i - P_d\right) \tag{3}$$

Where, P_f is penalty factor. But we can also solve the optimization problem without a penalty function by employing the constraint directly in the algorithm we used for the optimization problem. But this can be done only for a small number of constraints. If there are many constraints then this is very tough to include all the constraints in the algorithm itself, and then we have to use penalty function to handle the large number of constraints.

Every hour, the EMS needs to efficiently distribute the electricity that is needed among the available DERs to meet the load while keeping the value of OF as low as possible. An excellent optimizing approach can help you reach this goal.

PROPOSED ALGORITHM

The power scheduling problem is hard. Also, this does not follow a straight line, thus meta-heuristic algorithms are helpful since they use random patterns to move across the search space and avoid local minima. This project has come up with a new optimizer called the memory-based genetic algorithm (MGA). It finds the optimal way to distribute electricity among multiple distributed energy resources (DERs) while keeping production costs as low as possible.

Genetic Algorithm

Genetic algorithms (GAs) are numerical optimization techniques derived based on principles of natural selection and genetics. The approach is universally applicable to a vast array of challenges. In contrast to certain methodologies, their potential has seldom been exaggerated, and they are employed to address actual issues on a daily basis. Nonetheless, Genetic Algorithms were fundamentally conceived by a single individual, John Holland, in the 1960s.

Genetic algorithms are search algorithms that are based on the ideas of natural selection. They combine the "survival of the fittest" rule for string structures with a systematic yet random way of sharing information to make a search algorithm that has some of the creative qualities of human search. In each generation, a novel assembly of artificial entities (strings) is generated utilizing components from the most fit of the previous generation, with sporadic incorporation of additional elements for experimentation. Although randomized, genetic algorithms do not constitute a mere random walk. They effectively utilize existing data to hypothesize fresh search points with anticipated enhanced performance. The genetic algorithm can be utilized to address several optimization issues that are ill-suited for conventional optimization methods, including those with discontinuous, non-differentiable, stochastic, or extremely nonlinear objective functions. With the help of evolutionary algorithm, we can also solve mixed integer programming problems often. This seems which certain components are constrained to be integer valued. A standard genetic algorithm necessitates:

1. A genetic depiction of the solution domain, and
2. A fitness function to assess the solution space.

A conventional representation of each candidate solution is as a bit array. Arrays of various sorts and structures can be utilized in a fundamentally similar manner. The primary attribute that renders these genetic representations advantageous is their simply alienable components, attributable to their fixed size, which simplifies crossover processes. Variable-length representations can be utilized; however, the implementation of crossover becomes more intricate in this scenario.

Tree structures are examined in genetic programming, whereas graph-based representations are investigated in evolutionary programming; a combination of linear chromosomes and trees is analyzed in gene expression programming.

To execute GA, the subsequent actions should be utilized:

- *Step 1: Initialization:* A random group of chromosomes is created to show possible solutions. Each chromosome has power levels for distributed energy resources (DERs). A 100×6 matrix is utilized to solve this problem. It was made with MATLAB's rand (m, n) function. Each gene stands for the output of one DER at a certain hour. This initialization makes sure that the solutions are different and that the search space can be explored in a wide range of ways.
- *Step 2: Evaluating the Objective Function:* An objective function is used to rate each chromosome based on how well it meets load requirements while keeping power generating costs as low as possible. Fitness scores show how well a chromosome does its job. This fitness guides selection and reproduction by favoring superior options. Both the chromosomes of the parents and the chromosomes of the children pass on information to the next generation.
- *Step 3: Assign Memory (MGA Feature):* MGA has a direct memory part that keeps track of the chromosome that does the best in the population. This stored solution affects the next generation by mixing its genes with those of certain parents. This memory is refreshed as generations change to keep the best solutions. It makes searches more intense and speeds up convergence.
- *Step 4: Selection:* The selection process uses methods like tournament, roulette wheel, or rank selection to find parent chromosomes that are fit. Fitter chromosomes are more likely to be chosen, which helps the greatest traits survive. The roulette mechanism utilized here picks people based on how fit they are. This phase makes the crossover mating pool.
- *Step 5: Crossover:* Crossover takes genes from two chosen parents and mixes them to make new babies. In this procedure, single-point crossover is used 90% of the time. This means that a random site is chosen and gene segments are swapped. This helps pass on traits that work well to the following generation. It lets you look for new solutions while keeping the ones that work.
- *Step 6: Mutation:* Mutation makes random alterations to the genes of the progeny. These changes happen with a low chance (usually 0.05). It keeps genetic diversity in the population, which stops premature convergence. In this case, real-valued gene values are changed a little bit within the authorized limitations. Mutation makes things stronger and expands the search area.
- *Step 7: Offspring Generation Evaluation:* The same fitness function that was used to evaluate the first population is used to evaluate the new offspring. This tells you if the offsprings are better

than the current solutions. High-performing children are chosen to be part of the next generation. It makes it possible to keep track of progress all the time.

- *Step 8: Replacement:* Replacement decides which chromosomes stay in the population and which ones are thrown away. A steady-state technique is utilized, in which only the worst solution is replaced with a better child. This keeps the population steady while also making it better. It keeps top people and always brings in better candidates.
- *Step 9: Ending:* The algorithm runs for a set number of generations or until it stops getting better after a few tries. This keeps the quality of the solution while making the computer work faster. The maximum number of generations is the only reason for stopping in this investigation. The best-performing chromosome is the final output, which shows the optimum way to send electricity.

Pseudo Code

Let us Discuss Pseudo code of MGA algorithm used in MATLAB:

```
“Generate N viable chromosomes at random.
Compute the objective function of chromosomes.
Commit to memory the optimal chromosomal.
For i=1: maximum number of generations,
For j=1: N% Selection operator,
        Generate a random number between 0 and 1.
        Apply roulette wheel approach.
        Transfer the winner chromosome to matting pool.
End.
for k=1: N/2% crossover operator,
        Apply MGA crossover (single point crossover).
End.
        Alter the produced chromosomes using the mutation operator.
Assess progeny generation.
Revise memory.
Identify the optimal chromosome from the parental specimens.
Select the worst chromosome among offspring.
Substitute the least favorable progeny with the most exemplary parent.
Convey progeny to the subsequent generation as progenitors.
End”.
```

RESULTS AND DISCUSSION

To assess the efficacy of MGA in optimally distributing the required electrical power across distributed energy resources (DERs), a microgrid comprising three wind farms, two photovoltaic (PV) plants, and one combined heat and power (CHP) system has been analyzed. This system comprises six decision variables: the generated electricity of wind plant 1, wind plant 2, wind plant 3, PV plant 1, PV plant 2, and CHP. Table 2 presents the rated capacity of a system comprising three wind plants, two photovoltaic plants, and one combined heat and power plant.

It is presumed that at each hour, the available Distributed Energy Resources (DERs) can supply the necessary power shown in Table 3.

Table 2. Installed Capacity of System.

Plant Type	Rated Capacity
Wind Plant	750 kW
PV plant	200 kW
CHP plant	1000 kW

Table 3. Shows the demanded power at each hour.

Hour	1	2	3	4	5	6
Load (kW)	1471	1325	1263	1229	1229	1321
Hour	7	8	9	10	11	12
Load (kW)	1509	1663	1657	1643	1643	1652
Hour	13	14	15	16	17	18
Load (kW)	1666	1639	1642	1640	1676	1920
Hour	19	20	21	22	23	24
Load (kW)	2214	2382	2382	2327	2174	1903

The rated capacities of the wind plants, photovoltaic (PV) plants, and combined heat and power (CHP) systems in the microgrid are 750, 200, and 1000 kW, respectively. These variables enable the microgrid to operate in island mode [11]. The EMS is apprised of the required power and the maximum output capacity of each DER. It can promptly resolve the optimization problem and ascertain the appropriate power scheduling of distributed energy resources (DERs). The peak accessible power of DER for each hour is presented in Table 4. The information came from the study by Cristoni *et al.* [2].

The parameter setting of algorithm is as follows for both cases:
MGA: Population size =100, maximum number of generations =1000, crossover probability =0.9 and mutation probability =0.05.

The algorithm is executed 20 times every hour to achieve satisfactory results, and the top performing algorithms are presented in Table 5. Amount of renewable energy sources, the MGA algorithm's performance is evaluated in two different scenarios.

To test how well MGA works, we take a look at Figures 2 and 3.

- *Case-1:* which involves one combined heat and power (CHP) generation and four renewable generators. It is presumed that the renewable generators can be sent.
- *Case-2:* In this case, four CHP generators and two renewable generators are considered to calculate the performance of MGA. In this case, renewable generators are considered non-dispatchable so they are assumed to run on their maximum. Cost of generation for renewable generating plants will be fixed and independent of generation.

In example 1, the total cost of generating from MGA is $ 883.878. Which is the lowest cost when compared to other sources? For scenario 1, it takes an average of 2.03 sec to solve the scheduling problem.

Performance of GA showing summary of 20 test run is following for **case-1**.

Performance of GA showing summary of 20 test run is following for **case-2**.

Table 4. GA summary for case-1.

Hour (h)	Avg. time (s)	Avg. fit	Worst fit	Std. fit	Best fit.	Avg. itr	Median
1	0.233792	27.883088	27.97867	0.03489	27.83777	139.400	27.8768
2	0.172499	24.890549	25.00302	0.05004	24.84366	121.550	24.8726

Table 5. GA summary for case-2.

Hour	Avg. time (s)	Avg. fit	Worst fit	Std. fit	Best fit.	Avg. itr	Median
1	0.104294	120.55679	120.5573	0.00019	120.5566	152.050	120.556
2	0.103965	109.05868	109.0600	0.00037	109.0584	125.850	109.058

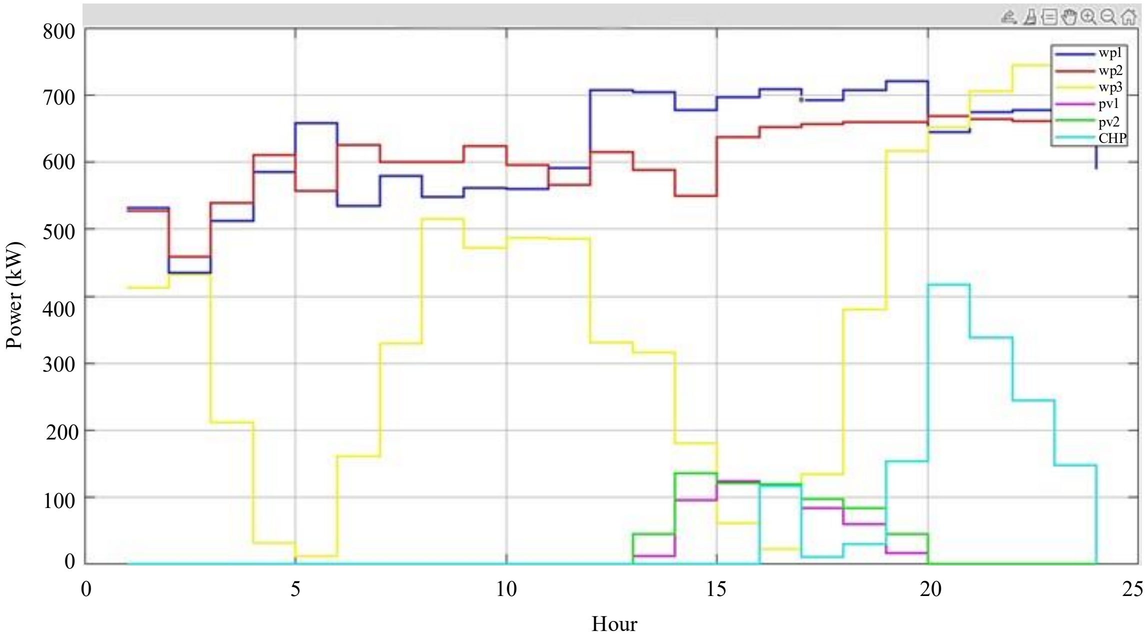

Figure 2. Optimal power scheduling obtained by MGA for case-1.

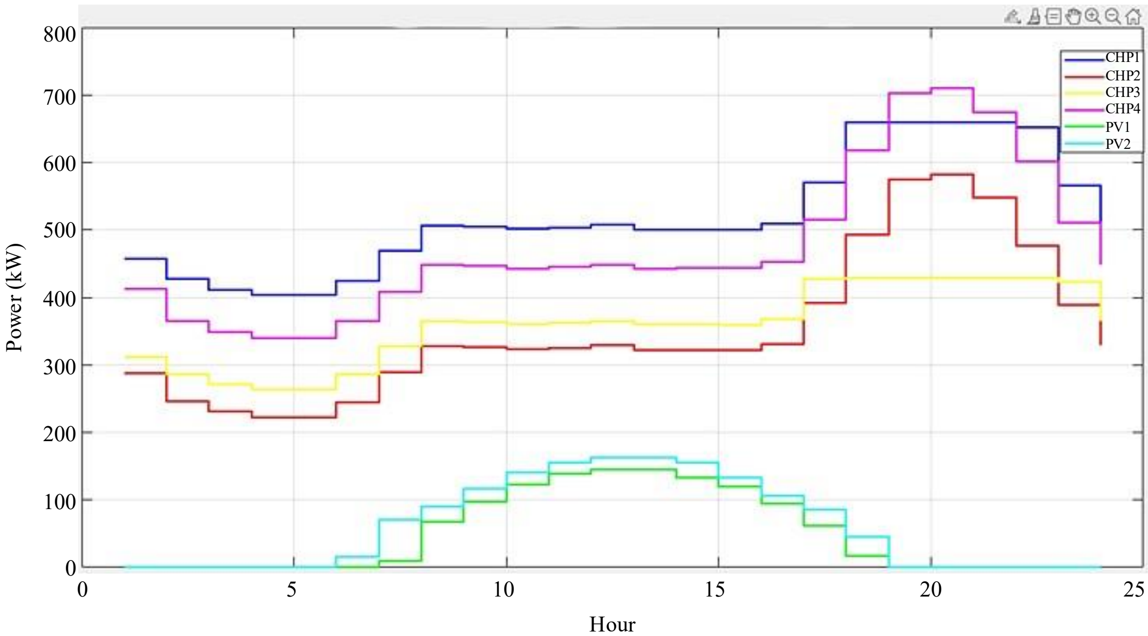

Figure 3. Optimal power scheduling obtained by MGA for case-2.

In short, the Memory-Based Genetic Algorithm (MGA) did well at scheduling in both dispatchable and non-dispatchable situations. Case 1 has a lower cost profile than Case 2, which gets the most out of renewable resources. There is a definite trade-off between using green energy and being flexible. Also, the fact that MGA can find almost the best solutions in less than 0.3 sec each time shows that it is a good choice for usage in real-time microgrid energy management systems. Overall, the results show that MGA is a good optimization framework for modern smart microgrids' economic scheduling.

Future Scope of Study/Work

"The proposed MGA approach has shown promising results in static microgrid scenarios. However, future work can focus on dynamic, real-world integration and multi-objective optimization s to make it more useful in industry."

Right now, the work is being done with simulations. The MGA method could be used in real-time Energy Management Systems (EMS) for microgrid operations in the future. The system will be more reliable and flexible when it comes to scheduling if it has battery storage and models how the battery charges and discharges. Using approaches like NSGA-II or MOPSO, you can get MGA to work for more than one purpose. These methods would take into account cost, pollution, and reliability [12–14].

In the future, researchers will be able to use MGA along with prediction algorithms for things like solar radiation, wind speed, and load demand. This will help them deal with the unexpected behaviors of renewable energy sources (RES) better. Using MGA with other optimization methods like PSO, Ant Colony, or Fuzzy logic can also speed up convergence and improve the quality of the results [15]. The project could be expanded to include the coordination of many microgrids, with a focus on cooperative scheduling and peer-to-peer energy trading. As smart grids become more common, cybersecurity and fault-tolerant scheduling are two features that may be added to MGA-based energy management systems (EMS) to protect against data threats and problems. Future studies could look into modelling carbon emissions and the environmental benefits of making renewable energy sources more efficient.

CONCLUSION

The MGA algorithm is used in this study to plan the generation in a microgrid that uses both traditional and renewable energy sources. Two alternative scenarios are looked at. In the first case, it is thought that renewable energy sources can be dispatched, as shown by Cristoni *et al.* [2]. Taking this instance into account, we were able to get the best schedule using the MGA algorithm while keeping costs as low as possible. Just like the cost of typical thermal power plants, the cost of renewable energy generation plants, such as photovoltaic and wind power plants, is thought to depend on how much power they make. Another problem is that they are not working at their best generation. The cost of installation and maintenance is what mostly affects the cost of generation in renewable power plants. This means that the cost of generating does not rely on how much electricity is made.

In the second scenario, renewable energy sources are not dispatchable when they are producing the most power. There are only fixed costs that are tied to renewable energy sources. These costs are the cost of investing, the cost of running the business, and the cost of keeping it up. We use the MGA approach to find the best way to schedule things in this case.

The results show that the Memory-Based Genetic Algorithm (MGA) does a good job at lowering generation costs while still meeting the system's needs and load demand. MGA can be used with a wide range of microgrid sizes and types, showing that it can be used in real-world power systems. The analysis that compares dispatchable and non-dispatchable scenarios shows how the properties of RES affect the best scheduling and cost dynamics. The results back up the claim that making the most of non-dispatchable renewable energy is good for the environment and the economy. The fact that the standard deviation is low throughout 20 test runs suggests that MGA gives findings that are always the same, no matter how it is set up. MGA strikes an excellent balance between optimization quality and calculation time, making it a strong choice for scheduling applications that need to happen in real time or close to real time. This work gives a strong base for more research into hybrid optimization methods, demand-side integration, and real-time EMS deployment.

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