Dynamic Economic Scheduling Strategy for a Stand-alone Microgrid System Containing Wind, PV Solar, Diesel Generator, Fuel Cell and Energy Storage: A Case Study

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Abstract. Efficient dynamic economic scheduling for a microgrid is essential to ensure optimal energy utilization and sustainability. In this paper, a day-ahead optimal dynamic scheduling for a stand-alone microgrid containing wind, PV solar, fuel cell, diesel generator and energy storage system is implemented. The primary objective of the dynamic economic scheduling is to minimize the energy production cost, maximize the energy storage system economic benefit and enhance the utilization of the renewables in the microgrid. The Genetic Algorithm (GA) optimization approach is proposed to solve the economic scheduling problem. Fluctuations of the load demands and renewables in the microgrid are considered and relevant predictions have been made to surmount these fluctuations. The proposed economic scheduling strategy has been tested on a case study microgrid in stand-alone mode (Goldwind Microgrid System, Beijing, China). Simulation results have demonstrated that the proposed approach can solve the day-ahead scheduling problem in a reasonably fast computation time. To validate and compare the performances of the proposed strategy, simulation results were also obtained using Pattern Search (PS) optimization technique. Comparisons of simulation results demonstrate the effectiveness of the proposed GA-based dynamic economic scheduling in attaining a minimum total cost of energy production within a short computation time.

1. Introduction

Microgrid is an aggregate of interconnected loads and distributed energy resources (including microturbines, fuel cells, diesel generators, energy storage, renewable energy resources, and all other kinds of distributed energy resources) at distribution level with distinct electrical boundaries that has black start capacity and can operate either in isolated or non-isolated mode. The transmission and distribution over capacity and expensiveness to secure or to expand, the electric and fuel gas prices fluctuations, the power quality, efficiency and reliability issues, cyber and physical security attacks, technological innovations of renewable energy resources are some of the influencing factors for the current shift of the world’s energy industry from large interconnected and centralized power systems to the decentralized small power systems called microgrids. Advanced control technologies that can
combine several generation systems and energy storage units together in self-contained manners as microgrid architecture are emerging to offer electricity customers the opportunity to access reliable and secured electricity locally.

Wind and photovoltaic solar (PV) as the main renewable energy resources, and conventional generation sources such as microturbine (MT), fuel cell (FC) and diesel engines (DE) are the primary distribution generation (DG) resources used in microgrids. These energy sources together with energy storage system (ESS) can support each other to compensate for the intermittent nature of the renewables, and thereby enhance the system reliability and energy sustainability as much as possible. Microgrids can be operated in self-contained manner (isolated microgrids) for electrifying off-grid remote areas, islands, military bases, institutions and industries that are far from the main grid, [1], [2]-[5], or to supply a group of loads in cities, in grid-connected mode of operation [6] and [7].

Robust economic dispatching strategy for microgrids is essential to ensure economic energy utilization and energy sustainability in the smart grid context. As a result of the alternating nature of the renewable energy resources used in microgrids and the electricity price fluctuations in the main grid, economic dispatching is a complex software structure that needs accurate predictions of the load demands and renewable energy resources within the microgrid. The conventional and classical optimization methods are not efficient and fast enough to be used for real-time optimization of this complex economic dispatching problem. Consequently, at the present time, the implementation of intelligent and modern optimization methods for economic dispatching of microgrids has become the key research aim in the field [1], [6]-[12].

This paper intends to apply a heuristic modern optimization method, Genetic Algorithm (GA) [13], for day-ahead economic scheduling of an isolated microgrid, which runs once in a day followed by heuristic hourly decision adjustments based on real-time renewable generations and load demands in every hours of the day. A real industrial microgrid (Goldwind Smart Microgrid System), in Beijing, China, in stand-alone mode, is considered to deliver the power demand requirements of the various loads within the company (Goldwind Science and Etechwin Electric. Co., Ltd.), shown in Fig. 1.

![Figure 1. Configuration of the stand-alone microgrid under study.](image)

The main components of the system are wind energy conversion system (WECS) that utilizes a permanent magnet synchronous generator (PMSG), three solar PV systems, fuel cell, diesel generator, a lithium-ion battery (Li-Ion) as ESS. The actual ratings of the components as shown in Fig. 1 are used in this study.
Besides, another direct search optimization method, Pattern Search (PS) was also implemented to validate the dispatch results obtained using GA. Neural networks based day-ahead forecasting of the wind power, PV solar power and the load demands have been carried out using data obtained from the microgrid supervisory control and data acquisition (SCADA) system and numerical weather prediction (NWP) weather prediction results around the microgrid installation site. These forecasting values were used as input variables in the economic scheduling simulation studies, using MATLAB/Simulink as the simulation environment.

The objective function for both optimization methods (GA and PS) is modified in every hour, during which the load demands and generations are supposed to be invariant. The Li-Ion storage unit was used to ensure long-term energy sustainability and to supply the power demanded during each hourly time interval to support the energy imbalance caused by sudden changes in load, wind speed, solar irradiation or other weather parameters. In this paper, a 24-hour simulation studies were carried out to show the work done on dynamic economic dispatching for isolated microgrid. The rapid convergence and global optimality of the GA [13], and the simulation results obtained indicate the robustness of the proposed economic dispatching strategy for microgrids.

This paper is organized as follows. Section 2 presents the objective and constraint function formulations. In Section 3, GA is briefly discussed and the proposed economic scheduling strategy is presented. The case study simulation results are discussed and comparison is provided in Section 4, and finally the paper is concluded in Section 5.

2. Optimization Model for the Dynamic Economic Scheduling Problem

The objective problem of the optimization model for dynamic dispatching in isolated microgrid with the prescribed setting, shown in Fig. 1, is formulated in this section. The microgrid, considered in this research paper, operates in isolated mode which can neither send power to the main grid nor receive power from the main grid, and thus the load demands in the microgrid are satisfied by its local generations. During all the operational periods, the microgrid is expected to minimize the energy production cost within it, maximize the economic benefits of the Li-Ion energy storage unit and ensure the renewable energy utilization to the maximum possible extent.

This objective function is subjected to four decision variables: the power operating points of the diesel generator and the fuel cell, the charging or discharging power of the energy storage unit and its state of charge. The associated constraint functions considering the DGs’ capacity and operational limits, the energy storage unit charging and discharging power limits and its state of charge (SOC) conditions, and all other technical requirements within the microgrid are also built in this section.

2.1. Objective Function Formulation

Some prerequisite information for a day-ahead economic scheduling in microgrids should be known in advance [14] and [15]. This information is as follows:

- Day-ahead hourly load forecast
- Day-ahead hourly wind power forecast
- Day-ahead hourly PV power forecast
- Conventional DGs’ cost functions and power limits
- ESS charging/discharging power limits and SOC conditions

In this scheduling optimization model, the simulation time interval is taken as one hour; thus the 24-hours ahead renewable generation and load demand forecasts are also given in one hour time interval.

Objective function:

$$\text{Min} \sum_{t=1}^{n} \sum_{i=1}^{m} \left(F_i \left(P_i(t)\right) + SC_i(t)\right)$$  \hspace{1cm} (1)
Where, \( n \) is the number of time intervals for a scheduling day; \( m \) indicates the number of all types of conventional and dispatchable units within the microgrid.

\[ \tau_i(t) = 1, \text{ if the } i\text{th dispatchable unit is in operation; } \]
\[ \tau_i(t) = 0, \text{ if the } i\text{th dispatchable unit is OFF at time } t; \]

The conventional DGs cost functions are given as follows:

\[ F_i(P_i(t)) = b_i P_i(t) + c_i, \text{ Fuel cell} \]
\[ F_i(P_i(t)) = a_i P_i(t)^2 + b_i P_i(t) + c_i, \text{ Diesel engine} \]

Here, \( a_i, b_i \) and \( c_i \) are the corresponding cost function parameters of each conventional DG in the microgrid. \( SC_i(t) \) is the start-up cost function of each conventional DG and is given by:

\[ SC_i(t) = sc_i, \text{ if } \tau_i(t) - \tau_i(t-1) = 1 \]
\[ SC_i(t) = 0, \text{ otherwise} \]

Where, \( sc_i \) is the start-up cost of the \( i \)th conventional DG unit.

### 2.2. Constraint Functions Formulation

The objective function formulated above is subjected to the following constraints including DGs and ESS capacity and operational limits, and all other technical requirements within the microgrid;

- **Power output of the \( i \)th unit at time \( t \):**
  \[ p_i^{\min} \leq P_i(t) \leq p_i^{\max} \]  \( (2) \)

- **Load demand and generation balance:**
  \[ \sum_{i=1}^{m} P_i(t) = P_{load}(t) - P_{wind}(t) - P_{pv}(t) - P_{ess}(t) \]  \( (3) \)

- **ESS charging/discharging power output:**
  \[ p_{ess}^{\min} \leq P_{ess}(t) \leq p_{ess}^{\max} \]  \( (4) \)

\( P_{ess}(t) > 0, \) ESS is discharging power;
\( P_{ess}(t) < 0, \) ESS is charging power;
\( P_{ess}(t) = 0, \) ESS is inactive/not in operation

- **ESS dynamic operation performance:**
  \[ SOC(t + 1) = SOC(t) - \frac{\eta_i \cdot P_{ess}(t)}{C_{ess}} \]
  \[ SOC_{\min} \leq SOC(t + 1) \leq SOC_{\max} \]  \( (5) \)

Where, \( \eta_i \) is the charging or discharging efficiency of the ESS; \( C_{ess} \) denotes the rated capacity of the ESS; \( P_{load}(t), P_{wind}(t) \) and \( P_{pv}(t) \) respectively represent the predicted load demands, wind generation and PV solar generation at time \( t \). Thus, the decision variables that need to be determined are the power outputs from the dispatchable DGs \( P_i(t) \) (for \( i = 1, 2, \ldots, m \)), the ESS charging or discharging power output \( P_{ess}(t) \) and its state of charge \( SOC(t) \) at the same time \( t \).

### 3. Proposed Optimal Scheduling Strategy

The proposed economic scheduling strategy for the isolated microgrid, with the prescribed setting above, has the following main goals:

1. Minimize the total cost of energy production;
2. Maximize the renewable energy resources utilization;
3. Maximize the economic benefit of the Li-Ion storage;
4. Maximize the Li-Ion life by monitoring its SOC and charging/discharging power;
5. Electrify dumping and testing loads when the load demands are fully satisfied and the Li-Ion is fully charged in case of excess renewable generations;
6. Reduce the use of the fuel fired conventional DGs by enhancing the renewable DGs utilization for less carbon emission.

Fig. 2 illustrates the information flows of the proposed scheduling system, which a scheduling center converts to output commands for dispatchable DGs output power, ESS optimal charging/discharging power and load monitoring action (shed, shift or dump). Decisions are based primarily on renewable generation and load demand forecasts. These decisions are generated in this paper for a day-ahead time horizon on one hour interval basis.

3.1. Genetic Algorithm (GA)

Most practical optimal design engineering problems are described by mixed continuous-discrete variables, and discontinuous and con-convex design domains. If traditional and standard nonlinear optimization techniques are implemented for this sort of engineering problem they will be inefficient, computationally expensive, and, in most cases, find a relative optimal solution that is closest to the starting point [16]. Genetic algorithms (GAs) are more suitable for solving such engineering problems, and in most cases they are able to find the global optimal solution with a high degree of probability. GAs were first presented systematically by Holland [17]. The GA basic ideas of analysis and design based on the concepts of biological evolution can be found in the work of Rechenberg [18].

GAs were inspired by Darwin’s theory of survival of the fittest. They are based on the principles of natural selection and genetics. The natural genetics fundamental elements—reproduction, crossover, and mutation—are used in the genetic search process. GAs differ from the classical techniques of optimization in the following aspects [16]:

![Figure 2. Information flow of the proposed dynamic scheduling strategy.](image-url)
1. A population of initial points is used for kicking off the procedure instead of a single design point, thus GAs are less likely to get trapped at a local optimum.
2. GAs do not use the derivatives of the objective function, only the objective function values are used in the search procedure.
3. The design variables in GAs are coded as strings of binary variables that correspond to the chromosomes in natural genetics. Thus the search technique is naturally suited for solving discrete and integer programming engineering problems. The string length can also be varied to attain any desired resolution in the case of continuous design variables.
4. In every new generation, a new set of strings (offspring) is produced by using probabilistic transition rules, not deterministic rules.

Fig. 3 shows a flowchart diagram of GA.

4. Case Study and Simulation Results
The stand-alone Wind-PV-DE-FC-Li-Ion microgrid in this research study is designed to deliver power to an industrial company, Goldwind Science and Etechwin Electric Co., Ltd., in Beijing, China. The generation capacity limits of the DGs in this microgrid are provided in Table 1, and the dispatchable DGs cost function parameters are also given in Table 2. The 24-hours ahead hourly load demand forecast for a typical day in the microgrid is shown in Fig. 4.

The predicted wind and PV generations, for the same typical day, are also shown in Figs. 5 and 6, respectively.

Fig. 7 shows the GA-based optimal energy scheduling for the same typical day, and the corresponding state of charge of the Li-Ion battery is shown in Fig. 8.

As depicted in Figs. 4 to 8, there is a high generation of wind energy and zero PV solar generation during the first six hours (12am - 6am) of the simulation period. In this period, the generation from the wind energy completely supplies the load demands and charges the Li-Ion battery which was at its minimum SDC (20%) before the simulation started, and all the conventional DGs are off (zero power) to minimize the fuel cost. The Li-Ion battery continuously charges (shown in Fig. 7 as negative power)
and reaches its maximum storage capacity (800 kWh or 100% maximum SOC), shown in Fig. 8, at 6am, and its charging power comes to zero (not in operation or inactive).

Table 1. DGs installed capacity.

| DG       | No. of Units/Systems | Unit/System Power Capacity (kW) | Total Power Capacity (kW) |
|----------|----------------------|---------------------------------|---------------------------|
|          |                      | Min Power                       | Max Power                 |
| FC       | 1                    | 10                              | 100                       |
| DE       | 1                    | 10                              | 200                       |
|          |                      | 10                              | 300                       |
| PV       | 4                    | 0                               | 100                       |
|          |                      | 0                               | 50                        |
|          |                      | 1                               | 30                        |
| Wind     | 1                    | 0                               | 2500                      |
| LI-Ion battery* | 1 | -200                        | 200                       |

* Li-Ion: SOC_{min} = 20%, SOC_{max} = 100%, C_{ess} (Capacity) = 800 kWh, η = 1

Table 2. Dispatchable DGs cost function parameters.

| DG       | Cost Function Parameters | Start-up Cost ($) |
|----------|---------------------------|-------------------|
|          | a ($/kWh)^2    | b ($/kWh) | c ($/h) | |
| FC       | 0              | 0.0164    | 3.68    | 18    |
| DE       | 0.00025        | 0.0156    | 0.3312  | 23    |

Figure 4. Forecasted load demand.
Figure 5. Forecasted wind power generation.

Figure 6. Forecasted PV solar power generation.

Figure 7. Dynamic economic scheduling using GA.
Since 7am, the wind generation gets down to zero while the PV source starts generating power. As the power generation from the renewables is insufficient to supply the load demands during this time, the DE and FC start operation to support the PV source. The Li-Ion battery sends or discharges power to the microgrid during this period to reduce the fuel cost. The Li-Ion battery continuously discharges (shown in Fig. 7 as positive power) and reaches its minimum storage capacity (160 kWh or 20\% minimum SOC), shown in Fig. 8, at 12pm and its discharging power becomes zero.

To minimize the cost of energy production, the Li-Ion battery is not in operation or inactive (shown in Fig. 7 as zero power) since 12pm; until it will be charged again by an available excess renewable generation in the microgrid and its SOC is kept at its minimum value of 20\%. The PV source together with the conventional DGs supplies the load demands from 12pm to 7pm and becomes zero at 7pm. The load demands are solely supplied by the DE and FC from 7pm to 12am as shown in Fig. 7.

In order to validate and compare the performances of the proposed GA-based dynamic economic dispatching strategy, a PS-based dynamic economic dispatching for the same microgrid and system parameters was obtained. Fig. 9 shows the PS-based optimal dynamic energy scheduling simulation result for the same typical day, and the Li-Ion battery state of charge using this approach is also shown in Fig. 10.

Figure 8. SOC of Li-Ion battery obtained using GA.

Figure 9. Dynamic economic scheduling using PS.
Figure 10. SOC of Li-Ion battery obtained using PS.

The hourly energy production costs obtained using both optimization approaches are shown in Fig. 11. As seen in this figure, the energy production cost is zero until 6am as there is enough generation from the renewables and the fuel fired conventional DGs are off; moreover, it’s clearly seen that the GA obtains the minimum energy production cost almost for all of the operation hours throughout the day.

Figure 11. Comparison of hourly energy production cost.

The total energy production cost for the whole day and the hourly average cost by both methods are also presented in Table 3. As shown in Table 3, the GA-based economic scheduling strategy has given a lower cost of energy production than the PS-based dynamic scheduling approach.

| Algorithm | Energy Production Cost ($) |
|-----------|---------------------------|
|           | Hourly Average Cost       | Daily Total Cost  |
| GA        | 16.2225                   | 389.3402          |
| PS        | 23.0382                   | 552.9169          |
Table 4 gives the total computation time taken by both dynamic scheduling optimization approaches in a Matlab/Simulink simulation environment (using Intel (R) core (TM i5-5200 CPU, 2.20GHz processor, 4GB RAM, and 64-bit operating system computer).

Table 4. Computation time.

| Algorithm | Total (for 24-hour ahead scheduling simulation) Computation Time (second) |
|-----------|---------------------------------------------------------------|
| GA        | 1.6824                                                        |
| PS        | 3.9452                                                        |

The GA-based strategy has allocated the dynamic economic schedule within a short period of time compared to the PS-based scheduling approach as given in Table 4 above.

5. Conclusions

GA-based dynamic economic scheduling strategy for a stand-alone microgrid containing wind energy conversion system, PV solar, diesel generator, fuel cell and Lithium-ion battery was presented in this paper. The proposed economic scheduling strategy takes into account the variation of load demands and intermittency of renewable energy resources in the microgrid, and thus appropriate day-ahead forecasts have been made to withstand these fluctuations. Simulation results confirm the suitability and possible advantages of the developed dynamic economic scheduling model in minimizing the total daily energy production cost, maximizing the energy storage economic benefits, and enhancing the utilization of renewable energy resources in the microgrid. To test and validate the proposed economic scheduling strategy performances, simulation results were also carried out for the same microgrid system using pattern search (PS) optimization technique. Comparison of simulation results demonstrate the robustness of the proposed GA-based dynamic economic scheduling in obtaining minimum cost of energy production. Furthermore, the proposed approach results global optimum solutions and converges rapidly that shows its capability for real time dynamic dispatching of microgrids.

References

[1] A.T.Eseye, Jianhua Zhang, Dehua Zheng, and Dan Wei, “Optimal Energy Management Strategy for an Isolated Industrial Microgrid Using a Modified Particle Swarm Optimization,” IEEE 2016 International Conference on Power and Renewable Energy, pp. 494 - 498, Shanghai, China, October 21-23, 2016.

[2] C. Wang, M. H. Nehrir, C. M. Colson, and J. Li, “Power management of a stand-alone hybrid wind-microturbine distributed generation system,” in Proc. Power Electronics and Machines in Wind Applications (PEMWA 2009), Jun. 24–26, 2009, pp. 1–7.

[3] R.-J. Wai, C.-Y. Lin, R.-Y. Duan, and Y.-R. Chang, “High-efficiency power conversion system for Kilowatt-level stand-alone generation unit with low input voltage,” IEEE Trans. Ind. Electron., vol. 55, no. 10, pp. 3702–3714, Oct. 2008.

[4] F. Valenciaga and P. F. Puleston, “Supervisor control for a stand-alone hybrid generation system using wind and photovoltaic energy,” IEEE Trans. Energy Convers., vol. 20, no. 2, pp. 398–405, Jun. 2005.

[5] C. Wang and M. H. Nehrir, “Power management of a stand-alone wind/photovoltaic/fuel cell energy system,” IEEE Trans. Energy Convers., vol. 23, no. 3, pp. 957–967, Sep. 2008.

[6] Abinet Tesfaye Eseye, Dehua Zheng, Han Li, and Jianhua Zhang, “Grid-price Dependent Optimal Energy Storage Management Strategy for Grid-connected Industrial Microgrids”, 9th Annual IEEE Green Technologies Conference (GreenTech), Denver, Colorado, USA, March 29-31, 2017.

[7] Han Li, Abinet Tesfaye Eseye, Jianhua Zhang, and Dehua Zheng, “Optimal Energy
Management for Industrial Microgrids with High-Penetration Renewables”, *Journal of Protection and Control of Modern Power Systems (PCMP)*-Springer, vol. 2, no. 1, April, 2017.

[8] V. Miranda and H. P. Sio, “Economic dispatch model with fuzzy wind constraints and attitudes of dispatchers,” *IEEE Trans. Power Syst.*, vol. 20, no. 4, pp. 2143–2145, Nov. 2005.

[9] C. L. Chen, “Simulated annealing-based optimal wind-thermal coordination scheduling, generation,” *Transmission & Distribution, IET*, vol. 1, no. 3, pp. 447–455, May 2007.

[10] Abinet Tesfaye Esseye, Jianhua Zhang, and Dehua Zheng, “Optimal Operational Planning for Microgrids under Grid-connected and Islanded Operation Modes”, *CSEE Journal of Power and Energy Systems (JPES)*. (Accepted for publication)

[11] C. Chun-Lung, “Optimal wind-thermal generating unit commitment,” *IEEE Trans. Energy Convers.*, vol. 23, no. 1, pp. 273–280, Mar. 2008.

[12] J. Hetzer, D. C. Yu, and K. Bhattarai, “An economic dispatch model incorporating wind power,” *IEEE Trans. Energy Convers.*, vol. 23, no. 2, pp. 603–611, Jun. 2008.

[13] Yiwei Ma, Ping Yang, Hongxia Guo and Yuewu Wang, “Dynamic Economic Dispatch and Control of a Stand-alone Microgrid in DongAo Island,” *J Electr Eng Technol (JEET)*, vol. 10, pp. 30-40, Oct, 2015.

[14] Zheng Zhao, “Optimal Energy Management for Microgrids”, PhD Dissertation, Electrical and Computer Engineering, Clemson University, Clemson, south Calorina, USA, January 2012.

[15] Alberto Borghetti, Mauro Bosetti and Samuele Grillo, "Short-term scheduling and control of active distribution systems with high penetration of renewable resources," *IEEE Systems Journal*, vol. 4, No. 3, September, 2010.

[16] Singiresu S. Rao, *Engineering Optimization: Theory and Practice, Fourth Edition*, John Wiley & Sons, Inc., 2009.

[17] J. H. Holland, *Adaptation in Natural and Artificial Systems*, University of Michigan Press, Ann Arbor, MI, 1975.

[18] I. Rechenberg, *Cybernetic Solution Path of an Experimental Problem*, Library Translation 1122, Royal Aircraft Establishment, Farnborough, Hampshire, UK, 1965.

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