GIET UNIVERSITY JOURNAL, 2022, VOL.2, NO.2, PP. 5
Manuscript received 5th May, 2023; revised 29th May, 2023; Accepted 15th April , 2023

Genetic Algorithm based demand side management for dynamic economic dispatch of microgrid system

Anshu Singh,GIET University, Gunupur, Odisha

Amitesh Kumar, GIET University, Gunupur, Odisha

Anshu Priya Yadav,GIET University, Gunupur, Odisha

Rakesh Sahu , GIET University, Gunupur, Odisha

Bishwajit Dey, GIET University, Gunupur, Odisha

***Abstract*—The amount of load required fluctuates from hour to hour in a typical microgrid (MG) arrangement. The power system utilities set the price of electricity at various periods of the day based on the load-demand curve's peaks and valleys. Electricity pricing based on time-of-use (TOU) is the term used to describe this procedure. It is possible to divide the hourly basis load demand into elastic and inelastic categories. Demand side management (DSM) shifts elastic loads to low demand hours during peak hours, when the utility charges more, in order to save costs. The demand price elasticity is then used to create the whole demand model. In order to reduce total costs associated with employing loads in MG structures, the study offers an intelligence-technique based DSM, keeping in mind that 10% to 40% of the total load within an MG structure within an hour is made up of elastic loads. Seven different scenarios, including DSM initiatives, are analyzed, and they include a range of grid participation and power market pricing tactics. The outcomes for each MG demonstrate the relevance and suitability of the suggested DSM strategy in terms of cost savings**.

Keywords: Microgrid; Demand-side management; Economic Load Dispatch; Dynamic Economic Load Dispatch; Genetic Algorithm

I. INTRODUCTION

Using the development of clean energy technology, they are receiving progressively utilized inefficient load dispatch (ELD)(ELD). A distributed system's various generating units do not share and deliver the same amount of load, which is reflected in the ELD concept. Rather, it distributed many loads is based on the respective Cost is an issue in order to equal the system's minimum generating cost. In addition, for any grid to function properly, the total energy demand must match the total energy output [1]. The notion ELD can be used roughly into dynamic ELD and static ELD (StELD) based on load demand (DyELD). Although DyELD when discussing ELD scenarios, the load demand fluctuates for a specified period, StELD when discussing ELD scenarios, the load demand remains constant. Due to the significantly less stringent amount of limitations, like ramp rates, banned operation areas, etc., StELD is relatively straightforward DyELD, however, is a more challenging

optimization issue. Here is so that DyELD can manage temporal and distributed energy resource (DER) limitations in addition to StELD constraints [4]. The duration of DERs, from start to finish as well as the process of power storage devices being charged and discharged pose the biggest problem in determining the best solution to DyELD difficulties.

A. Related Work

Many research projects have conducted to assure the wise renewable energy creation and distribution energy, which can guarantee a good revolutionary influence in the framework of the economy of power production. Also, it is crucial because of rising fuel costs and environmental concerns. A thorough research of ELD can therefore be seen as a critical issue in the power industry. The standard computational techniques can be used with ease when dealing with cost functions that are smooth, continuous, and non-convex [5]. However, because to the addition of established physical restrictions, an ELD issue is portrayed with an uneven and convex surface. form, complicating things and thus the failure of typical approaches [6]. Traditional optimization techniques like recursive lambda, the dynamic programming, the gradient approach, and frequently used to address smooth ELD problems [7]. Yet, the accurate modelling of ELD difficulties in real-world settings necessitates a high level of precision and the meticulous management of multiple restrictions. This makes the objective function possible with extra complexity that undermines established patterns methodologies for obtaining the ideal answer [8]. The cost curve's shape is one of the main obstacles to the application of these approaches. Contrary to the system dimensionality, which heavily influences dynamic programming, the cost curve has no impact on it. Moreover, for big systems, dynamic programming has a long computation time [9, 10]. The relevance Using meta-heuristic techniques in the field of addressing the nonlinearity issue in ELD in recent years has gained relevance while keeping in mind all the shortcomings of the conventional methodologies [11]. Many evolutionary techniques emerged throughout time in the field of ELD problem research. These evolutionary techniques were developed with inspiration from the development of life [12]. As an illustration, the (GA) [13] is a genetic algorithm. a well-known employing evolution used is built on the idea of cell reproduction and its well-known genetics to address the ELD problem.

DERs combine generators that use fossil fuels with RES such micro-turbines, solar generators, fuel cells, batteries, and flywheels, among others [14]. Microg the demand points for load rids (MGs) are a type of DER that distribute the load demand points over a small geographic area. MGs can operate in grid-connected or mode islanded. Considering that there are purchase and sell options available to or from the utility, the grid-connected form is favored. In the event of an unanticipated network failurethe utility-connected DER has the choice of getting grid power support. Researchers' interest in the field of MG energy management has greatly increased as a result of this. To lower A matrix real-coded based GA, an imperialist competitive algorithm (ICA), and an on-grid mode MG's manufacturing costs are shown in [15,16]. The authors undertook a number of case studies to demonstrate how well the algorithm handled the small operating window intermittent DERs price of electricity, and load volatility. In [17], the cuckoo search algorithm has been used, which performs better than differential evolution (DE) and particle swarm optimization (PSO) methods. A DyELD issue is being identified based on the wind speed in an islanded MG with two wind turbines. It has been reported in [18] that an adaptive modified PSO can be used to obtain an ELD solution in an on-grid mode MG. The authors of [19] use a tailored ICA method to examine economic goals and goals related to emission dispatch.

In [20–22], a three-unit island MG with PV and wind generating uses the for economical dispatch, emission shipment, and combined economic emission dispatch, the modified harmonic search method, the interior search method, and the whale optimization method, respectively (CEED). The best value is chosen for CEED after numerous price penalty elements have been analyzed. Modified personal best PSO, artificial fish swarm algorithm and memory-based GA are utilized in [23–25] for an islanded MG system incorporating 2 PVs, 3 wind turbines (WTs) and 1 combined heat and power (CHP) (CHP). The MPBPSO demonstrated the best outcome in terms of minimization of the cost.

B.THE RESEARCH PAPER'S ORDER

The remainder of the text is presented in the following sequence. In Section 2, the role of fitness that must be minimized is considered. This part also examines the DSM-based MG energy management's limitations on equity and inequality for the test systems. Three low-voltage connected to the grid residential and commercial MG are presented in Part 3. buildings that are used as case studies. The planned work is inferred in Section 4. The paper's final part makes suggestions for additional work.

II. Demands Side Management

A. Strategy Incorporated in DSM

Over the past few years, research on MG energy management with an emphasis on economic activities has progressively increased. The description of the economic activity for an MG structure is tasteless without the idea of DSM. When the DSM is used, most of the research articles discussed in the related work section can be produced for less money. strategy. With the DSM technique, elastic loads are identified and transferred as efficiently as possible to the area of the load curve where the electricity usefulness charge is lower. Peak demand is reduced as a result. As a result, the utility's load factor increases, even while the overall load demand at the end of a scheduling term—which, for most utilities, is a day—remains same. In Figure 1, some of the load shaping techniques used by DSM are shown, including load shifting, valley filling, peak clipping, flexible load shaping, strategic conversion, and strategic expansion. Basic-level types comprise the first three techniques. The system design and operation of the three additional, more complex ways is used to alter the overall load demand shape. The load shifting strategy, which combines many loading management techniques, is in fact the most popular. consumption.

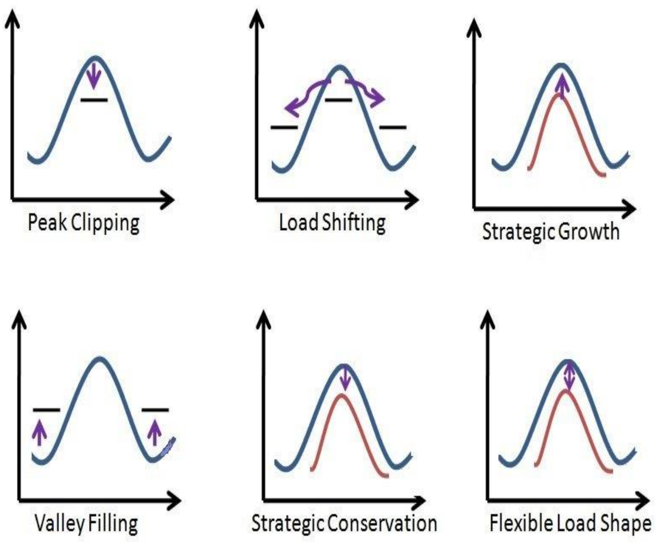

Figure 1. Load shaping methods of DSM.

B. How to Use the DSM Method to Get a Restructured Load Model

Phase 1: The various There are T hours of loading data entered.

Phase 2: For the next T hours, the power market rate based on time of utilization (TOU) is entered.

Phase 3: The DSM engagement percentage is input (in case the elastic loads are not determined in before).

Phase 4: Considering the DSM percentage involvement, the quantity of elastic loads, LD_{el}^{tm}, is determined. For instance, P% DSM participation suggests that P% of the hourly load demand is elastic load. Remaining (100−P) percent is in elastic load, LD_{el}^{tm}. Following the calculation, the elastic loads are scheduled optimally.

Phase 5: The minimal, maximal & average of both the in elastic weights are calculated.
Phase 6: The optimization approach is then used, as shown in (13), subject to the restrictions in (14), and (15), where C tm grid denotes the TOU-based electricity price at time tm, LDtm in denotes the inelastic load at time tm, and $LD^{\max}$ denotes the maximum load density. The maximum allowable elastic load is known as el.
Phase 7: The DSM technique recognizes the reconstructed load demand idea as the sum of the hourly inelastic load demand with the elastic maximum load that is optimized.

$$Min[C_{grid}^{tm} * (LD_{in}^{tm} + LD_{el}^{tm})] \quad \textbf{(1)}$$

$$0 \le LD_{el}^{tm} \le LD_{el}^{\max} \quad \textbf{(2)}$$

$$Total\ \ Demand = \sum_{tm=1}^{T} (LD_{in}^{tm} + LD_{el}^{tm}) \quad \textbf{(3)}$$

III.Proposed Algorithm: Genetic Algorithm

Genetic algorithms (GA) are a subset of evolutionary algorithms that are based on the principles of natural selection and genetics. GAs is used to solve optimization problems by mimicking the process of natural selection and the biological mechanisms of genetic recombination and mutation. The goal of a genetic algorithm is to find the optimal solution to a problem by generating a population of candidate solutions and repeatedly selecting the fittest individuals, reproducing them, and introducing genetic variation through mutation and crossover operations.

The basic components of a genetic algorithm include the population, fitness function, selection, crossover, and mutation. The population represents a set of candidate solutions to the problem being optimized. The fitness function evaluates how well everyone in the population performs with respect to the problem at hand. The selection process determines which individuals will be used for reproduction based on their fitness scores. The crossover operation involves selecting two individuals from the population and recombining their genetic information to create offspring. The mutation operation introduces random variations in the genetic information of an individual.

The effectiveness of a genetic algorithm depends on the quality of the fitness function, the selection method, and the mutation and crossover operations. The fitness function must accurately measure the performance of everyone in the population. The selection method should favor fitter individuals while still allowing for diversity in the population. The mutation and crossover operations should introduce sufficient variation to explore the search space effectively while avoiding premature convergence to suboptimal solutions. Genetic algorithms have been used to solve a wide range of optimization problems, including scheduling, routing, and packing problems, as well as in engineering, finance, and other fields. They have several advantages over traditional optimization methods, such as the ability to handle non-linear and non-convex functions, and the ability to search for multiple solutions simultaneously.

In summary, genetic algorithms are a powerful optimization technique that mimics the natural process of evolution to search for optimal solutions. They are particularly useful in problems where traditional optimization methods may struggle, and they have been successfully applied to a wide range of real-world problems. A flowchart for steps of GA implementation is shown in Figure 2.

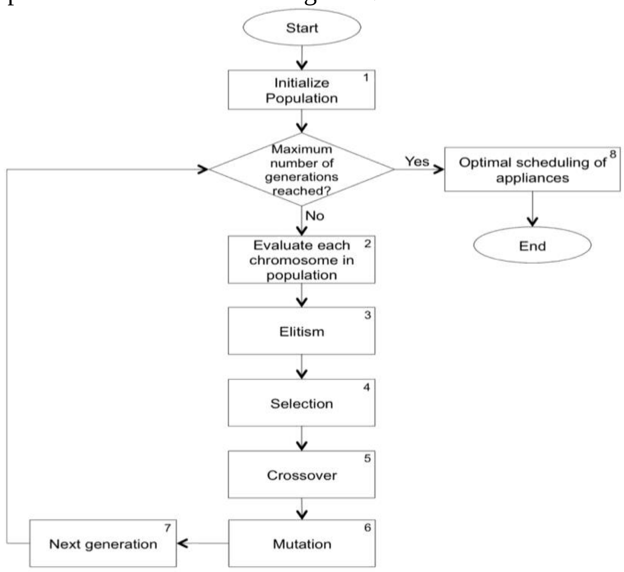

Figure 2: Steps for implementing Genetic Algorithm (GA)

IV.Results and Discussion

A 24 hours' load demand as shown in Figure 3 is considered for restructuring implementing various levels of DSM participation. the market price for electricity dependent on when it is used is shown in Figure 4. GA was implemented as optimization tool to restructure the forecasted load demand considering 10% to 40% DSM participation levels. The optimization was done using GA toolbox in MATLAB 2017 Intel Core i5 processor with 8GB of RAM installed in a laptop's participation levels indicate the amount of elastic loads every hour that can be rescheduled to those hours when the electricity market price is less. This has been described above in Section 2. The restructured dynamic load demand after the implementation of DSM from 10-40% is shown in Figure 5. The positive impacts of DSM implementation can be seen in Table 1 and are described below:

- The total load demand and average load demand model remains the same for any level of DSM participation.
- The peak demand reduced to as high as 4% when DSM level participations were implemented.
- The (LF) load factor (ratio of average demand to peak demand) increased gradually for various levels of DSM participation. The generation cost decreased from $4168 to $3985 when various levels of DSM participation were introduced.

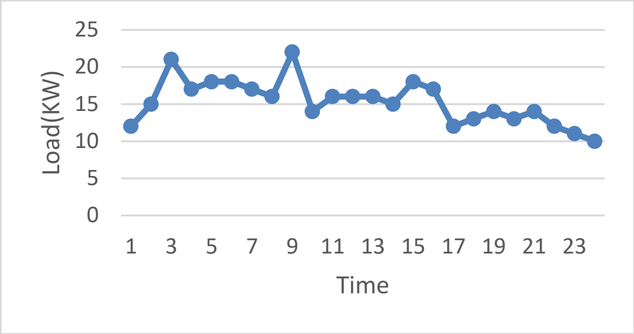

Figure 3: Dynamic Load demand with respect to time

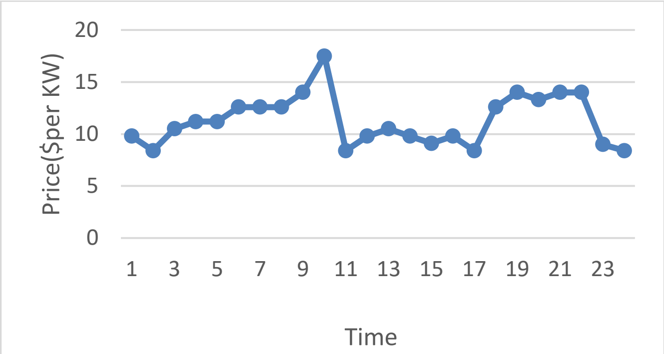

Figure 4: Electricity market price varying on Time of Usage basis

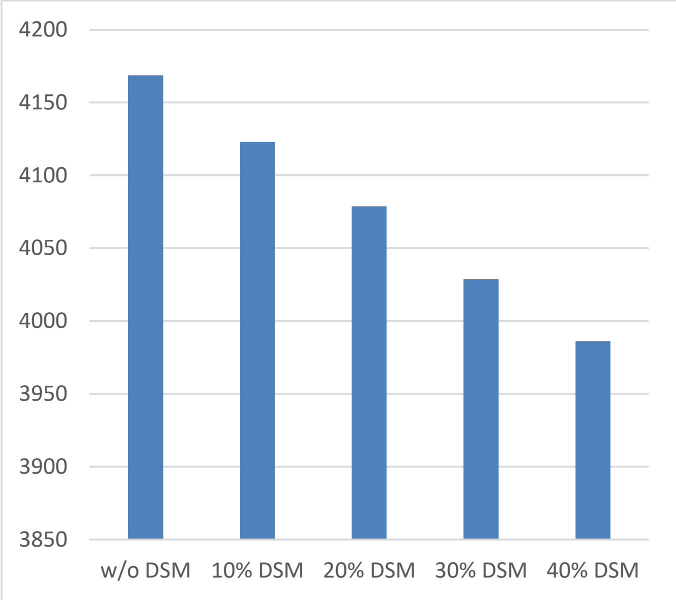

Figure 6: Decrement in generation cost due to DSM participation levels

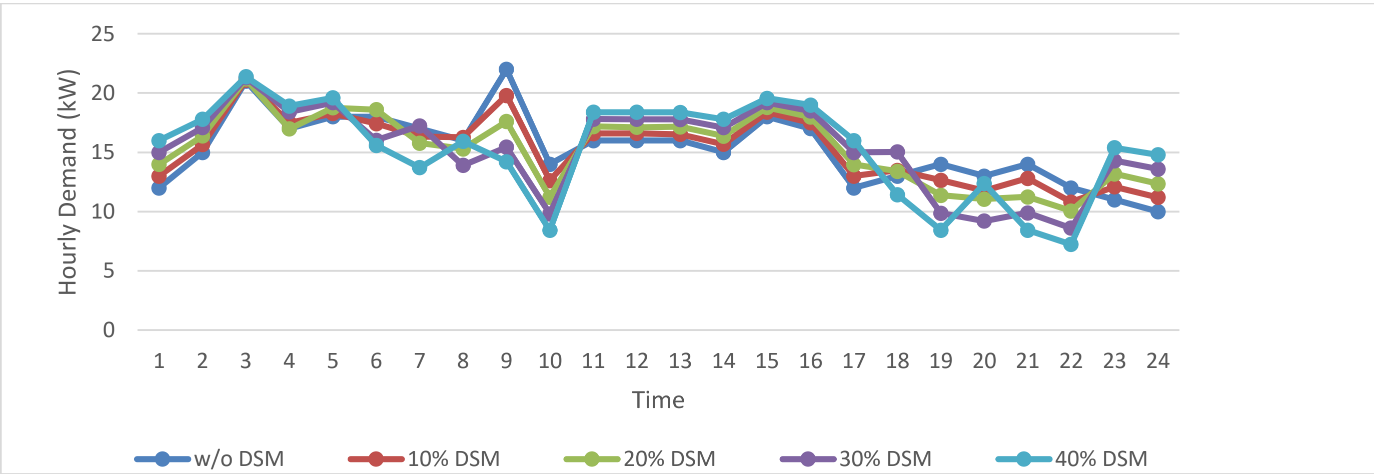

Figure 5: Dynamic Load demand for different levels of DSM participation

Table 1
Effects of DSM strategy on load demand

Demands	w/o DSM	10% DSM	20% DSM	30% DSM	40% DSM
Total	367	366.99	366.99	366.99	366.99
Peak	22	21.099	21.190	21.296	21.373
Avg	15.2	15.29	15.29	15.29	15.29
LF	0.6	0.7246	0.721	0.7179	0.7152
Peak reduc		4.09	3.67	3.19	2.83
Gen. cost	4168.8	4122.9	4078.606	4028.6157	3985.9738

CONCLUSION

Genetic algorithm was used to perform demand side management on dynamic load demand with time of usage (TOU) based electricity pricing. The elastic loads were gradually changed for 10-40% and the following positive impacts were observed:

a. The load factor was gradually increase from 0.695 to 0.71524 when the elastic loads were increased up to 40%.
b. The peak demand was reduced to 4.09% when DSM was implemented to shift the elastic loads from peak to off-peak periods.
c. The generation cost of the microgrid system was reduced from $4168 to $3986 when 40% elastic loads were considered. That is a 4.3% savings in the generation cost was realised.

ACKNOWLEDGEMENTS

We are very grateful to experts for their appropriate and constructive suggestions to improve this template.

REFERENCES

[1] Ghosh, B.; Dey, B.; Bhattacharya, A. Solving economic load dispatch problem using hybrid Krill Herd algorithm. In Proceedings of the 2015 International Conference on Energy, Power and Environment: Towards Sustainable Growth (ICEPE), Shillong, India, 12–13 June 2015.

[2] Yalcinoz, T.; Short, M.J. Neural networks approach for solving economic dispatch problem with transmission capacity constraints. IEEE Tran. on Pow. Sys. 1998, 13, 307–313.

[3] *Sahu, R., Panigrahi, P. K., & Lal, D. K. (2020, December). Control and protection of hybrid smart-grid power system: A review. In 2020 IEEE International Symposium on Sustainable Energy, Signal Processing and Cyber Security (iSSSC) (pp. 1-6). IEEE.*

[4] Dhillon, J.; Parti, S.C.; Kothari, D.P. Stochastic economic emission load dispatch. Elect. Pow. Sys. Res. 1993, 26, 179–186.

[5] Wang, C.; Shahidehpour, S.M. Ramp-rate limits in unit commitment and economic dispatch incorporating rotor fatigue effect. IEEE Tran. on Pow. Sys 1994, 9, 1539–1545.

[6] Kai, S.; Qing, L.; Jizhen, L.; Yuguang, N.; Ruifeng, S.; Yang, B. New combination strategy of genetic and tabu algorithm an economic load dispatching case study. In Proceedings of the 2011 Chinese Control and Decision Conference (CCDC), Mianyang, China, 23–25 May 2011.

[7] Bhattacharya, A.; Chattopadhyay, P.K. Solving complex economic load dispatch problems using biogeography-based optimization. Exp. Sys. with App. 2010, 37, 3605–3615.

[8] Sinha, N.; Chakrabarti, R.; Chattopadhyay, P.K. Evolutionary programming techniques for economic load dispatch. IEEE Trans. Evol. Comp. 2003, 7, 83–94.

[9] Daniel, L.; Chaturvedi, K.T.; Kolhe, M.L. Dynamic Economic Load Dispatch using Levenberg Marquardt Algorithm. Energy Procedia 2018, 144, 95–103.

[10] Sahu, R., Misra, S., Sandhya, Y. B., Panigrahi, P. K., & Prasad, G. S. (2023). Smart controller PV system for stochastic environmental condition. Materials Today: Proceedings, 80, 2553-2556.

[11] Hosseinnezhad, V.; Babaei, E. Economic load dispatch using θ-PSO. Int. J. Electr. Pow. Energy Syst. 2013, 49, 160–169.

[12] Yang, X.; Leng, Z.; Xu, S.; Yang, C.; Yang, L.; Liu, K.; Zhang, L. Multi-objective optimal scheduling for CCHP microgrids considering peak-load reduction by augmented ε-constraint method. Renew. Energy 2021, 172, 408–423.

[13] Nwulu, N.I.; Xia, X. Optimal dispatch for a microgrid incorporating renewables and demand response. Renew. Energy 2017, 101, 16–28.

[14] *Rakesh, S., Digbijoy, M., Tanushree, M., & Nishant, P. (2016). Designing and study standalone hybrid energy system: for technical institutes. Int J Inf Res Rev, 3(6).*

[15] Coelho, V.N.; Coelho, I.M.; Coelho, B.N.; Cohen, M.W.; Reis, A.J.; Silva, S.M.; Souza, M.J.; Fleming, P.J.; Guimarães, F.G. Multi-objective energy storage power dispatching using plug-in vehicles in a smart-microgrid. Renew. Energy 2016, 89, 730–742.

[16] Grefenstette, J.J. Genetic algorithms and machine learning. In Proceedings of the Sixth Annual Conference on Computational Learning Theory, Santa Cruz, CA, USA, 26–28 July 1993.

[17] Dutta, S.; Reddy, M.J.B.; Mohanta, D.K.; Kushwah, M.S.; Sadhu, P.K. μPMU-based intelligent island detection–the first crucial step toward enhancing grid resilience with MG. IET Sma. Gri. 2020, 3, 162–173.

[18] Chen, C.; Duan, S.; Cai, T.; Liu, B.; Hu, G. Smart energy management system for optimal microgrid economic operation. IET Renew. Power Gener. 2011, 5, 258–267.

[19] *Sahu, Rakesh, et al. "Smart Operations Of Smart Grids Integrated With Fuel Cell With Controlling Strategies" International Journal of Engineering and Advanced Technology, Volume-8 Issue-6, August, 2019. DOI: 10.35940/ijeat.F8635.088619.*

[20] Kasaei, M.J. Energy and operational management of virtual power plant using imperialist competitive algorithm. Int. Trans. Electr. Energy Syst. 2018, 28, e2617.

[21] Basu, M.A.; Chowdhury, A. Cuckoo search algorithm for economic dispatch. Energy 2013, 60, 99–108.

[22] Moghaddam, A.A.; Seifi, A.; Niknam, T.; Pahlavani, M.R.A. Multi-objective operation management of a renewable MG (microgrid) with back-up micro-turbine/fuel cell/battery hybrid power source. Energy 2011, 36, 6490–6507.

[23] Rabiee, A.; Sadeghi, M.; Aghaei, J. Modified imperialist competitive algorithm for environmental constrained energy management of microgrids. J. Clean. Prod. 2018, 202, 273–292.

[24] Trivedi, I.N.; Jangir, P.; Bhoye, M.; Jangir, N. An economic load dispatch and multiple environmental dispatch problem so-lution with microgrids using interior search algorithm. Neur. Comp. App. 2018, 30, 2173–2189.

[25] *Sahu, R., Das, B., Sabat, R. R., & Swain, M. K. (2013). Hybrid Power Model of Renewable Energy Sources For On Grid Power Supply. International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, 2(11), 5466-5473.*

[26] Elattar, E.E. Modified harmony search algorithm for combined economic emission dispatch of microgrid incorporating renewable sources. Energy 2018, 159, 496–507.

[27] Faseela, C.K.; Vennila, H. Economic and emission dispatch using Whale Optimization Algorithm (WOA). Int. J. Electr. Comput. Eng. 2018, 8, 1297.

[28] Kumar, K.P.; Saravanan, B.; Swarup, K.S. Optimization of Renewable Energy Sources in a Microgrid Using Artificial Fish Swarm Algorithm. Energy Procedia 2016, 90, 107–113.

[29] Gholami, K.; Dehnavi, E. A modified particle swarm optimization algorithm for scheduling renewable generation in a mi-cro-grid under load uncertainty. Appl. Soft Comp. 2019, 78, 496–514.

[30] Askarzadeh, A. A Memory-Based Genetic Algorithm for Optimization of Power Generation in a Microgrid. IEEE Trans. Sustain. Energy 2017, 9, 1081–1089.