Application of intelligent scheduling to optimal power dispatch of wind Integrated power system

Alpesh Kumar Dauda*
Department of Electrical and Electronics Engineering
Sambalpur University Institute of Information Technology
Burla, Odisha, India
alpesh.d123@gmail.com

Ambarish Panda
Department. of Electrical and Electronics Engineering
Sambalpur University Institute of Information Technology
Burla, Odisha, India

Abstract— Due to the unpredictability of wind flow, accurate modelling of wind energy conversion systems (WECS) and their integration with traditional fossil fuel-based generation and the grid is essential. This research addresses the imperative issue of modeling the combined operation of a wind-thermal generation systems within an optimal power flow framework. The objective extends beyond cost minimization to include secure and stable voltage operation. To achieve this, a comprehensive approach is adopted, considering the dynamic nature of wind power generation and its impact on the overall system. To optimize the suitably specified objective, hybrid algorithms (HA) and Artificial bee colony (ABC) algorithms have been applied. The result shows that HA outperforms ABC algorithm in terms of finding the best solution for the configuration under consideration. IEEE30 bus power system is used for the analysis.

Keywords - *Wind integration; voltage security; power system operation; OPF; optimization.*

.

I. INTRODUCTION

The inconsistency of the WECS output poses significant scheduling issues for conventional generation units, potentially putting the system at risk. The authors have addressed the issue of wind power variability in [1]. In [2, 3, 4], the authors present a framework of associated costs related to wind power in wind integrated systems during under and over forecasts. Optimal power flow (OPF) problems have lately been handled using a variety of traditional and algorithms based on intelligent techniques [2-12]. All of these studies are aimed at resolving the OPF problem in thermal generation systems as well as minimizing system running costs and other difficulties. However, the technology under consideration in this proposed work is a wind+thermal generation system. Using a differential evolution approach, the author in [5] explores the OPF solutions for a conventional power generation system. The authors in [6] have presented a comparative evaluation of the economics and voltage security of BES integrated WP+PV+Thermal hybrid configurations with variable renewable energy penetration using modified Bacteria Foraging algorithm. In [7] proposes a Moth Swarm Algorithm (MSA) and Gravitational Search Algorithm (GSA) for determining the optimal control variable settings for the OPF problem in a power system. In [8, 9], the artificial bee colony (ABC) method is used as the basic optimizer for the control of the power system variable modifications in the OPF problem. Both continuous and discrete variables are included in the control variables. Hydropower is favoured as a versatile energy source to make up for the unpredictability of solar and wind energy [19].Panda et al. [20] used large-scale energy storage facilities in conjunction with intelligent scheduling techniques to simultaneously lower power loss, operational costs, and enhance voltage security for various hybrid power systems.

The suggested system's design challenge is framed as an optimization problem in an OPF framework [1], aiming to keep a desirable voltage profile throughout system operation while reducing the cost of WECS and conventional generators.

II. PROBLEM FORMULATION

A cost component could be added to the system generation cost to account for the intermittency of wind flow. This supplementary component, in addition to the generation cost, is aimed to reduce the cost of operation in the event of an unbalance between available and utilized wind power.

The problem is formulated as follows, taking into account all of the preceding facts:

Minimize

$$\mathbf{F = F_1 + F_2} \qquad (1)$$

The cost of wind-thermal power generator is represented by F1, whereas the cost of intermittent wind power generation is represented by F2.

The above components are mathematically interpreted as follows:

$$F_1 = \sum_{j}^{N_g} C_j(P_{gj}) \qquad (2)$$

The thermal units are denoted by subscript j, whereas the wind units are denoted by subscripts k and w. The cost of producing thermal energy is the first term in F1. These terms are explained as

$$C_j(P_{gj}) = a_j P_{gj}^2 + b_j P_{gj} + c_j \qquad (3)$$

where Pgj is the power output of the j[th] generator, while a_j, b_j and c_j are the j[th] thermal unit's cost coefficients.

Table.1 provides more information on the cost coefficients.

$$F_2 = \sum_{k}^{N_w} [C_{wk}(P_{wk}) + C_{p,wk}(P_{wk,av} - P_{wk}) + C_{r,wk}(P_{wk} - P_{wk,av})] \qquad (4)$$

The various components of F2 can be described as follows. The cost of purchasing wind power from a wind power producer is the 1[st] term of F2, the cost of underestimating available wind power is the 2[nd] term, and the cost of overestimating available wind power is the 3[rd] term.

$$C_{wk}(P_{wk}) = d_k P_{wk} \qquad (5)$$

The schedule power output of the k[th] wind unit is denoted by P_{wk}, and d_k is the direct cost coefficient associated with the k[th] wind generator. Equation (6) can be used to express the cost of underestimating available wind power.

$$C_{p,wk}(P_{wk,av} - P_{wr}) = K_{Pk}(P_{w\,av} - P_{wk})$$

$$= K_{pk} \int_{P_{wk}}^{P_{ko}} (w - P_{wk}) f_w(w)\,dw \qquad (6)$$

K_{Pk} in eq.(6), is the penalty cost coefficient and $f_w(w)$ is the probability density function of the wind power [4], also known as Weibull distribution function. P_{wk} is the scheduled, P_{ko} is the rated, and $P_{w\,av}$ is the available wind power from the kth wind power generator. Cost of over estimation may be expressed as

$$C_{R\,wk}(P_{wk} - P_{wk\,av}) = K_{Rk}(P_{wk} - P_{w\,av})$$

$$= K_{Rk} \int_0^{P_{wk}} (P_{wk} - w) f_w(w)\,dw \qquad (7)$$

The following constraints apply to the above-mentioned objective function, given by (1).

$$\sum_{j}^{N_g} P_{gj} + \sum_{k}^{N_w} P_{wk} = P_{loss} + P_{load} \qquad (8)$$

$$\sum_{j}^{N_g} Q_{gj} + \sum_{k}^{N_w} Q_{wk} = Q_{loss} + Q_{load} \qquad (9)$$

$$P_{gj}^{min} \le P_{gj} \le P_{gj}^{max} \qquad (10)$$

$$Q_{gj}^{min} \le Q_{gj} \le Q_{gj}^{max} \qquad (11)$$

$$V_j^{min} \le V_j \le V_j^{max} \qquad (12)$$

$$P_{wk} \le P_{wk}^{max} \qquad (13)$$

$$Q_{wk}^{min} \le Q_{wk} \le Q_{wk}^{max} \qquad (14)$$

In thermal generators, real power and reactive power are represented as P_{gj}, Q_{gj} respectively, in the preceding formulas (8)-(14), while in wind power units, the corresponding power are P_{wk}, Q_{wk}.

III. APPLICATION OF OPTIMIZATION TECHNIQUES

A. Artificial Bee Colony Algorithm

The artificial bee colony (ABC) algorithm is an optimization method based on the honeybee swarm's intelligent foraging behavior [8, 9]. Both discrete and continuous variables are included in the control variable. ABC algorithm is a population based algorithm that was inspired by the way honeybee swarms stumble upon their feed. The honeybee swarm is divided into two groups by this algorithm: worker bees and non-worker bees, which include observer bees and explorer bees. At regular intervals, spectator bees form around the worker bees. The created spectator bees are depicted in the next iteration if they locate the perfect fitness value among all the reproduced bees. The authors in [9] discussed a detailed flow chart that includes an explanation.

B. *HYBRID ALGORITHM*

The Hybrid Algorithm (HA) is created by combining GA's mutation techniques with a modified BFA strategy, first presented in [17] and later implemented in [2,3,4], in order to increase the optimization efficiency of both algorithms in particular specific applications. Reference in [17] can be used to access the original version of BFA. The enhanced and new version of BFA is comparable to the novel algorithm, with the exception of a few changes detailed in [2]. The authors in [12] provide a detailed explanation of the steps involved in HA. A comparison of HA and PSO was carried out in [12] to indicate the efficacy of Hybrid algorithm. In this work, the capability of HA is examined with ABC algorithm in a similar manner like [12] in order to better understand the operation in a hybrid power system.

IV. RESULTS AND DISCUSSION

The benchmark test system, the IEEE-30 bus power system, was used to validate the results[18]. Wind farms are installed on the fifth, eleventh, and thirteenth buses, replacing conventional generators. Each wind farm (WF) is made up of a number of wind turbines, or more precisely, wind turbine generators (WTG)[13-14]. The wind farm at bus no. 5 in this project consists of 20 WTG (one and all 2.5 MW), having a 50-megawatt (MW) capacity. In the same way, WF at bus numbers 11 and 13 has 7 WTG with a capacity of 5 MW, totaling 35 MW. Each wind farm (WF) is made up of multiple wind turbines and double-fed induction generators (DFIGs). The optimal schedule is obtained by solving OPF equations to optimise the objective function stated in the preceding section. A comparison analysis is conducted on two different optimization approaches applied to the objective function. Table 1 shows the optimum cost of generation determined with both HA and ABC algorithm. Table 2 lists the generating cost coefficients for the thermal units. The entire cost of power generation in the wind-thermal system is calculated for the goal indicated in (1) and optimised independently using HA and ABC algorithm. Figure 1 shows the convergence characteristics produced by GA and HA for the aforementioned objective function. The HA convergence point is 3081.12 \$/hr, whereas the ABC algorithm convergence point is 3086. 58 \$/hr. Thus, the effectiveness of HA is clearly portrayed in terms of obtaining most economic operating cost. It also indicates that annual savings in operating cost is around 4.78296×10^4\$/yr.

During the UE scenario, a voltage security analysis of system performance was performed under typical operating conditions. The voltage profile of the system has been illustrated in Fig.2 using the optimal generating schedule determined with HA and ABC algorithm separately. It clearly demonstrates that the HA optimised schedule outperforms the ABC algorithm schedule in terms of maintaining a better and more effective voltage profile on practically all bus in the system.

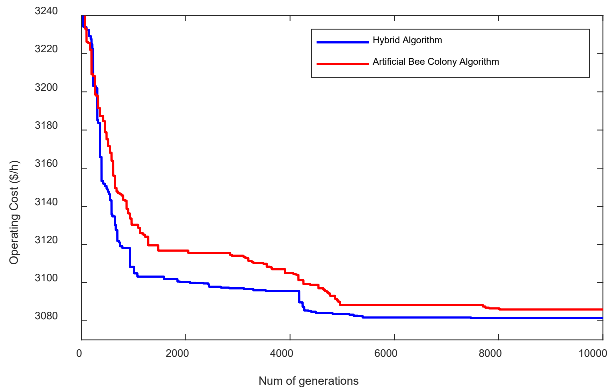

Fig.1.Convergence Characteristics of operating cost

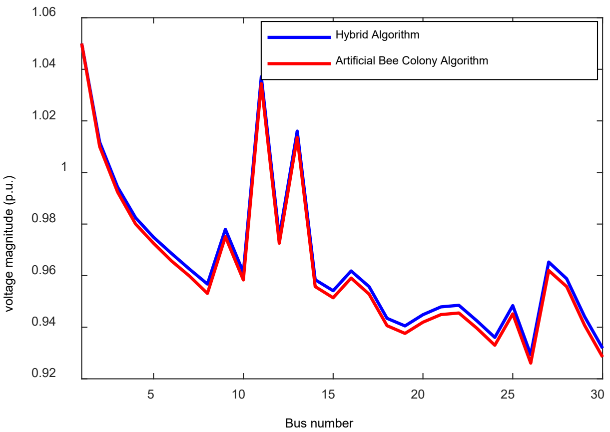

Fig.2. System voltage profile with HA and ABC algorithm optimized schedule

The HA improved generation schedule, as shown in both figures, has resulted in a significant increase in system voltage and a reduction in total system operation cost.

TABLE-1.OPTIMAL CONVERGENCE OF COST($/HR)

Method	Cost
HA	3081.12 $/hr
ABC algorithm	3086. 58 $/hr

TABLE-2. COST COEFFICIENTS OF THERMAL GENERATING UNITS

	Cost coefficients				
Generator No.	a_j	b_j	c_j	MIN LIMIT (MW)	MAX LIMIT (MW)
1	0.00974	2.5	0	50	200
2	0.0174	1.75	0	20	80
3	0.0624	1.0	0	10	40

V. CONCLUSION

In view of the volatility and volatile nature of available wind energy, it is important to plan power generation intelligently and effectively, especially if underestimated. This study seeks to achieve ideal voltage-secure operation while minimizing power generation costs.. In this case, HA and ABC algorithm approaches are used to test the running test system in operation. Both strategies are utilized to find an ideal operating schedule of the IEEE-30 bus power system in order to validate their effectiveness. In terms of achieving better convergence characteristics and delivering optimal generation scheduling that may provide an acceptable voltage for secure system operation, the HA is determined to be superior to the ABC algorithm. As a result, HA could be a potential solution for complicated power system analysis as well as a decision-making tool for power system operators in real-time operations.

REFERENCES

[1] Sanjari, M. J., Gooi, H. B., & Nair, N. K. C. (2019). Power generation forecast of hybrid PV–wind system. *IEEE Transactions on Sustainable Energy*, *11*(2), 703-712.

[2] Panda, A., & Tripathy, M. (2014). Optimal power flow solution of wind integrated power system using modified bacteria foraging algorithm. *International Journal of Electrical Power & Energy Systems*, *54*, 306-314.

[3] Panda, A., & Tripathy, M. (2015). Security constrained optimal power flow solution of wind-thermal generation system using modified bacteria foraging algorithm. *Energy*, *93*, 816-827.

[4] Panda, A., Tripathy, M., Barisal, A. K., & Prakash, T. (2017). A modified bacteria foraging based optimal power flow framework for Hydro-Thermal-Wind generation system in the presence of STATCOM. *Energy*, *124*, 720-740.

[5] Biswas, P. P., Suganthan, P. N., Mallipeddi, R., & Amaratunga, G. A. (2018). Optimal power flow solutions using differential evolution algorithm integrated with effective constraint handling techniques. *Engineering Applications of Artificial Intelligence*, *68*, 81-100.

[6] Dauda, A. K., & Panda, A. (2023). Impact of Small Scale Storage and Intelligent Scheduling Strategy on Cost Effective and Voltage Secure Operation of Wind+ PV+ Thermal Hybrid System. *Advanced Theory and Simulations*, *6*(1), 2200427.

[7] Shilaja, C., & Arunprasath, T. (2019). Optimal power flow using moth swarm algorithm with gravitational search algorithm considering wind power. *Future Generation Computer Systems*, *98*, 708-715..

[8] Adaryani, M. R., & Karami, A. (2013). Artificial bee colony algorithm for solving multi-objective optimal power flow problem. *International Journal of Electrical Power & Energy Systems*, *53*, 219-230.

[9] *Ettappan, M., Vimala, V., Ramesh, S., & Kesavan, V. T. (2020). Optimal reactive power dispatch for real power loss minimization and voltage stability enhancement using Artificial Bee Colony Algorithm. Microprocessors and Microsystems, 76, 103085..*

[10] Alanazi, M., Alanazi, A., Abdelaziz, A. Y., & Siano, P. (2022). Power Flow Optimization by Integrating Novel Metaheuristic Algorithms and Adopting Renewables to Improve Power System Operation. *Applied Sciences*, *13*(1), 527.

[11] Panda, A., Dauda, A. K., Chua, H., Tan, R. R., & Aviso, K. B. (2023). Recent advances in the integration of renewable energy sources and storage facilities with hybrid power systems. *Cleaner Engineering and Technology*, 100598.

[12] Panda, A., & Tripathy, M. (2016). Solution of wind integrated thermal generation system for environmental optimal power flow using hybrid algorithm. *Journal of Electrical Systems and Information Technology*, *3*(2), 151-160.

[13] Wadi, M., & Elmasry, W. (2021). Statistical analysis of wind energy potential using different estimation methods for Weibull

parameters: a case study. *Electrical Engineering*, *103*(6), 2573-2594.

[14] Usta, I. (2016). An innovative estimation method regarding Weibull parameters for wind energy applications. *Energy*, *106*, 301-314.

[15] Konak, A., Coit, D. W., & Smith, A. E. (2006). Multi-objective optimization using genetic algorithms: A tutorial. *Reliability engineering & system safety*, *91*(9), 992-1007.

[16] Glenn-Sttag, W., & El-Abiad, A. H. (1984). Computer Methods in Power System Analysis.

[17] Passino, K. M. (2002). Biomimicry of bacterial foraging for distributed optimization and control. *IEEE control systems magazine*, *22*(3), 52-67.

[18] M.A.Pai, Computer methods in power system analysis, TMH Publishers, 1996.

[19] Panda, A., Aviso, K. B., Mishra, U., & Nanda, I. (2021). Impact of optimal power generation scheduling for operating cleaner hybrid power systems with energy storage. *International Journal of Energy Research*, *45*(10), 14493-14517.

[20] Panda, A., & Mishra, U. (2023). An environmental optimal power flow framework of hybrid power systems with pumped hydro storage. *Journal of Cleaner Production*, *391*, 136087.