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A Smart Grid Demand-Side Management Program Using AI to Predict Renewable Energy

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Abstract: Modern technology has made it possible to harvest Renewable Energy Sources (RES) on a large scale. A sustainable method of generating electricity is projected to be Smart Grids (SGs), which mix traditional and RES sources. Additionally, all RES are affected by environmental factors, which alters the amount of power generated by these sources. Additionally, accessibility is based on yearly or daily periods. Although real-time demand forecasting is made possible by smart metres, accurate models that forecast the electricity generated by RES are also necessary. The reliability of grid stability, effective scheduling, and energy management are all guaranteed by prediction models (PMs). For instance, if the model predicts a period of Renewable Energy (RE), the SG must smoothly transition into the conventional energy source for that time and ensure that the electricity generated satisfies the anticipated demand loss. The research also recommends several learning-based PMs for sources of RE using open data sources and scheduling techniques for demand-supply matching. This study created a model that faithfully reproduces a microgrid, forecasts supply and demand, flexibly plans power delivery to meet demand, and provides practical insights about how the SG system functions. The Demand Response Programme (DRP) is also developed in this work employing cost-saving incentive-based payment packages. The test results are evaluated in several scenarios for the multi-objective ant colony optimisation algorithm (MOACO) with and without the input of the DRP to optimise operating costs.

Keywords: renewable energy; distributed energy resources; micro-grid system; deep learning; demand response programs; smart grid

1. Introduction

Because of increased awareness of Energy Consumption (EC) and production worldwide, the market share of renewable sources has been increasing. Renewable Energy Sources (RES) are predicted to outperform fossil fuels in monthly power generation. There is a departure from the industry’s restraint and unsustainable resources, and consumers and energy providers have developed using 23% green

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power. However, the infrastructure operations are complicated, and utility companies and consumers are challenged due to the inconsistency of market demand and supply of extensive energy that RES and utility companies and consumers can meet. The energy company applied Smart Grid (SG) technology to stabilise the Green Energy Supply (GES) and make RE trustworthy and future-proof. A traditional Distribution System (DS) supports the energy flow from suppliers to users. Energy transmission and distribution with SGs are performed using a SG as a one-way electrical interconnection system integrated with massive production points as the only energy source at multiple locations. The industries require multiple extra production points combined with the increased volume of smaller RE generation plants. The new paradigm could not be continued by the conventional method, which depends on the operator-enabled power system, and highly flexible operation management is allowed because a SG solution replaces it. Future SG-based DSs will also be able to meet the increased use of renewable Wave Swell Energy (WSE) sources that behave in a standard method that repeats itself. The operation's security may be endangered due to this [1]. There is a need for Advanced Measuring Infrastructure (AMI) [2] to guarantee the cost-efficient and secure operation of these systems and to use cutting-edge design for Distributed Energy Resources (DER) [3 - 4]. AMI provides smart meters, which have the features of remote control, monitoring, and readability, by creating bidirectional telecommunication between electricity companies and customers, embracing data collection and transmission by energy providers, information analysis and processing, and implementing EC management to ensure system reliability and balance supply and demand [5 - 6]. Since the environmental impact is reduced, the market situation, reliability, and service should be enhanced. An SG will incorporate information and Communications Technology (ICT) into each component, such as electricity generation, EC, and delivery. An SG makes the seamless integration of unreliable RES and the potential for efficient power distribution and delivery highly possible. The scale of SG adoption is the basis for efficiently incorporating RE into the energy sector, supporting technologies such as smart meters and the Internet of Things (IoT), and big data will drive it forward. While deploying RE systems, control is a complex aspect. For super-performance and reliable operations, WSE is required. By implementing digitally enabled SGs, such as the IoT, consumers and energy suppliers will be provided with advanced tools for monitoring and regulating SG performance [7]. It is performed by controlling multiple devices at production points and households.

2. RES Prediction

1.1. Solar Power Prediction (SPP)

The model is initialized by integrating Numerical Weather Predictions (NWP) to start with an ideal stage. Weather satellites and ground weather stations provide these weather predictions. Because of

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huge-scale forces, the predicted weather modifications, such as SP, speed, and clouds, can be assessed using standard operational NWP models at national centres [8]. However, the prediction of WP or SP resources, adapted to the WP or SP plant's particular application and the WP or SP plant's location, is permitted by personalized NWP. A chance to assimilate exclusive local observations at the neighbouring power plant is provided. NWP models vary in the model grid's resolution and spatial model domain [9]. The model grid's conventional spatial resolutions of 50 km for the global and approximately 2 km for the region are integrated with the global PM, i.e., globally and regionally, with an area-restricted MESO scale to operate. Well-designed global PMs forecast large-scale synoptic weather patterns. However, with less than 10 km of horizontal resolution, the regional models' current role is overtaken by the persistent hike in computer power [10].

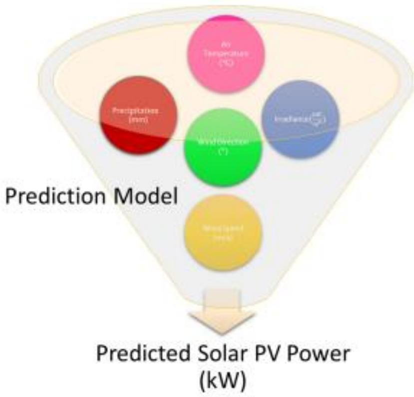

Figure 1. Solar PV-PM

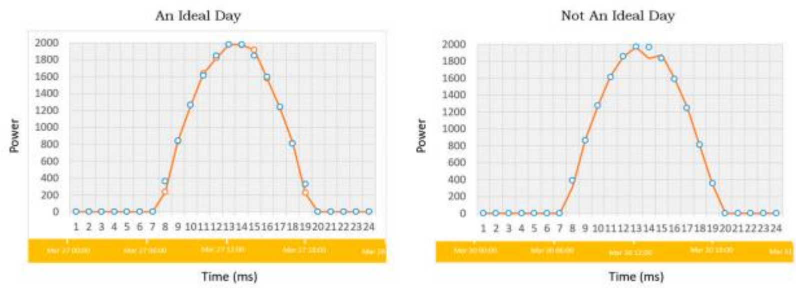

Figure 2. Illustration of an optimum day chosen on the left and a non-ideal day on the right (with a minor decrease at noon).

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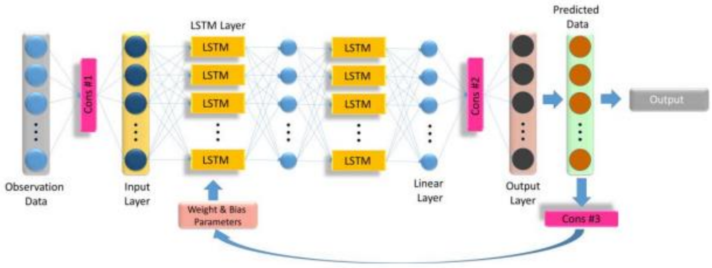

Figure 3. PC-LSTM architecture with three constraints.

PV panels near the ground surface gather solar energy, which is crucial for power generation. As a result, it is critical to mark periods with positive SP on the ground. Using hourly Surface Energy (SE) values, the DFM does this automatically. During training, the model only uses data from the marked periods [11]. In the prediction step, on the other hand, the resulting PV output will be computed correspondingly for periods when SE is predicted to be '00 . The efficiency of the PC-LSTM is increased to some extent by using fewer data points for model training. The Clipping Module (CM) is the second constraint included in the PC-LSTM; it is used to keep the model's output within a tolerable range during training and testing. Using natural science to analyse PV avoids physical obstacles such as negative power generation [12]. The model output should be positive because PV should be physically greater than '00 . As a result, the PC-LSTM output, yi , should satisfy the constraint in Equation (15).

The problem is looked at differently to refer to how the energy level, reserve, and DR schedules affect operating costs and to clear up any confusion between WP and SP resources.

Case 1: Assuming the operational cost without DRP.

Case 2: Assuming the operational cost of DRP.

In all scenarios, power-producing units should be able to engage in the SG depending on their practical and commercial qualities, and in the presence of increased generation and demand, energy is exchanged only with the utility through a Point of Common Coupling (PCC). To verify the model's effects, the proposed model was created using MATLAB R2022a software.

Case 1: Considering the cost of operations without the proposed DRP: From here,

the operational costs are minimised independently without considering the DR. Figure 3 illustrates the best power generation allocation for lower operating costs. It shows that the battery begins to be charged early in the morning when energy costs are low, and whenever energy costs are high, the utility obtains energy from SG, wherein CEs prioritize power usage only at the lowest quoted price. The outcomes in

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Figure 3 show that the SG does not seek SP and WP. As a result, when evaluating the reasonable operational cost, they will not get much consideration.

Case 2: Costs and functionality of operations using DR: With the help of DR, operating

costs are reduced independently. Figure 4 demonstrates the optimal power generation unit allocation for reducing operational costs. Although SP generation decreases from 4.54 to 3.15 kW, WP generation in the DRP decreases from 8.02 to 7.41 kW. These programs reduce SP and WP generation from 47.68 to 44.65 kW and 86.10 to 84.32 kW, respectively. Figure 5 shows how much energy a WT and solar cell produce when operational costs and DR are considered. Figure 6 shows that using DRPs limits the amount of WT and solar cells that can be made while also shifting demand from peak to off-peak times. When consumers take part in the DRP and say they will use less power at a specific time, the system operator can lower the power of the generating units.

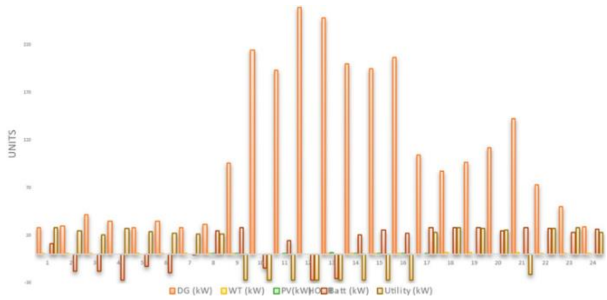

Figure 4. Energy resource scheduling without DR.

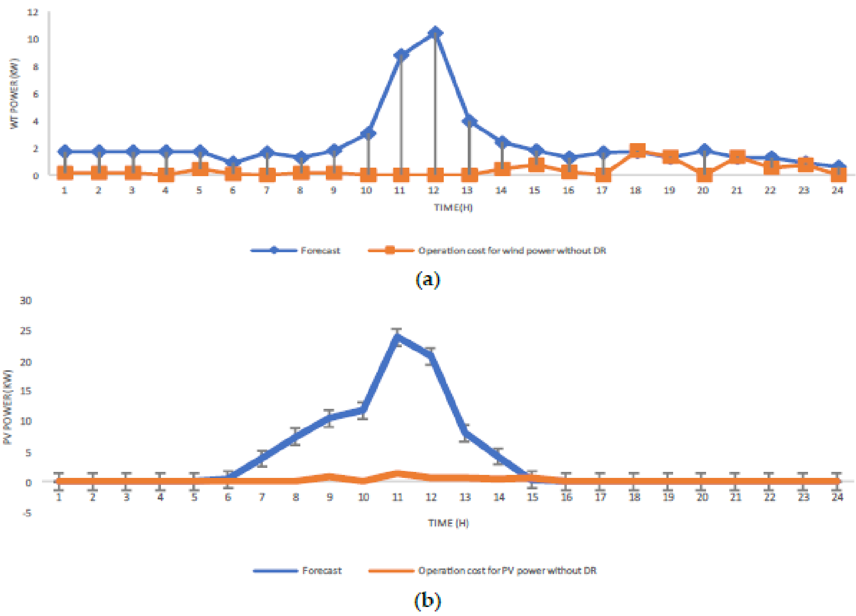

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Figure 5. Output power (**a**) WP; (**b**) PV power estimate without DR.

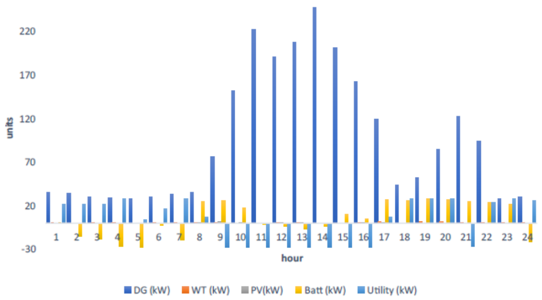

Figure 6. The operation cost of objective energy resource scheduling with DR.

The performance evaluation of MOACO is shown through a comparison of standard deviation. Out of 50 runs, it has a minimal standard deviation of 1 unit. Additionally, the computational speed is faster, such as 0.5 ms.

To validate the results, two more algorithms in the literature have been taken to solve the problem as given in Table 3. We have implemented Multi-Objective Flower Pollina- tion Algorithm (MOFPA) and Multi-objective Golden Flower Pollination Algorithm (MOGFPA) to validate the MOACO results. Comparatively, the standard deviation of MOACO is a lot less. At the same time, computation time is faster than the other two algorithms, as shown in the Figure 7.

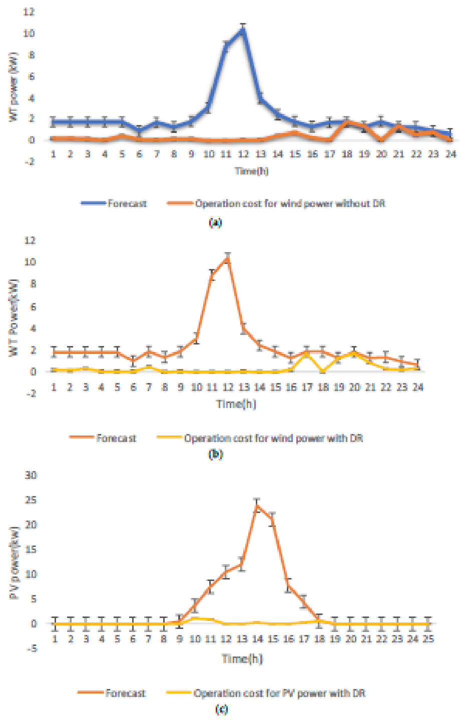

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Figure 7. Output power (**a**) Wind power estimate without DR; (**b**) Wind power estimate with DR; (**c**) PV power estimate with DR.

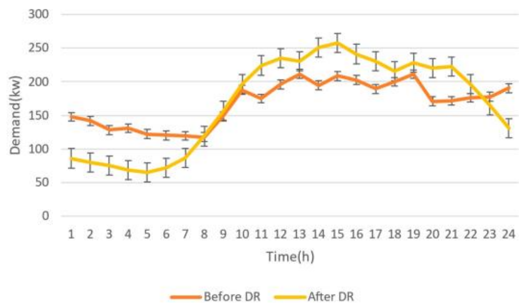

Figure 8. Pre- and post-DR load demand.

Table 3. Validation of MOACO with other algorithms.

Algorithms	Computation Time (ms)	Standard Deviation
MOFPA	2	5
MOGFPA	1	2
MOACO	0.5	1

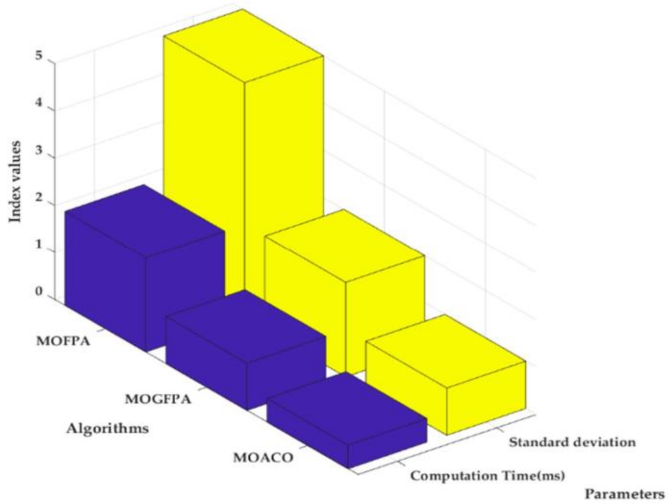

Figure 17. Comparative results of MOACO performance evaluation.

Conclusions

The Demand Response (DR) was used in this study to achieve the best demand-side management for the Smart Grid (SG) by compensating for the uncertainty caused by the generation of Wind Power (WP) and Solar Power (SP) in an optimisation function with two competing aims. The microgrid's overall running cost was evaluated in a variety of situations. The assessment of WP

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and solar cell power generation using Deep Learning (DL)-based Prediction Models (PM) was also provided. The possibility of energy exchange was considered for better SG operation. Based on incentive payments to control consumption, it is projected that consumers will participate in DRPs. The MOACO approach was used to resolve the supplied model and deliver an ideal result. The simulations showed that if clients use DR and deal with production losses Operating costs will be decreased as a result of the uncertainties in WP and SP. This could be improved in the future study scope using vehicle-to-grid systems for the best energy management and savings. Operations of aggregaters would likewise be taken into account for the SG's optimal operating circumstances.

References

1. Do Prado, J.; Qiao, W.; Qu, L.; Agüero, J. The Next-Generation Retail Electricity Market in the Context of Distributed Energy Resources: Vision and Integrating Framework. *Energies* **2019**, *12*, 491. [CrossRef]

2. Johnson, J.; Quiroz, J.; Concepcion, R.; Wilches-Bernal, F.; Reno, M.J. Power System Effects and Mitigation Recommendations for DER Cyberattacks. *IET Cyber-Phys. Syst. Theory Appl.* **2019**, *4*, 240–249. [CrossRef]

3. Zhang, Y.; Huang, T.; Bompard, E.F. Big Data Analytics in Smart Grids: A Review. *Energy Inform.* **2018**, *1*, 8. [CrossRef]

4. Palaniappan, S.; Asokan, R.; Bharathwaj, S.; Sujaudeen, N. Automated Meter Reading System—A Study. *Int. J. Comput. Appl.* **2015**, *116*, 39–46. [CrossRef]

5. Zakariazadeh, A.; Jadid, S.; Siano, P. Stochastic Multi-Objective Operational Planning of Smart Distribution Systems Considering Demand Response Programs. *Electr. Power Syst. Res.* **2014**, *111*, 156–168. [CrossRef]

6. Zakariazadeh, A.; Jadid, S.; Siano, P. Economic-Environmental Energy and Reserve Scheduling of Smart Distribution Systems: A Multiobjective Mathematical Programming Approach. *Energy Convers. Manag.* **2014**, *78*, 151–164. [CrossRef]

7. Rezaei, N.; Kalantar, M. Smart Microgrid Hierarchical Frequency Control Ancillary Service Provision Based on Virtual Inertia Concept: An Integrated Demand Response and Droop Controlled Distributed Generation Framework. *Energy Convers. Manag.* **2015**, *92*, 287–301. [CrossRef]

8. Blanc, P.; Espinar, B.; Geuder, N.; Gueymard, C.; Meyer, R.; Pitz-Paal, R.; Reinhardt, B.;

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 10, Iss 3, 2021

Renné, D.; Sengupta, M.; Wald, L. Direct Normal Irradiance Related Definitions and Applications: The Circumsolar Issue. *Sol. Energy* **2014**, *110*, 561–577. [CrossRef]

9. Chu, Y.; Pedro, H.T.C.; Coimbra, C.F.M. Hybrid Intra-Hour DNI Forecasts with Sky Image Processing Enhanced by Stochastic Learning. *Sol. Energy* **2013**, *98*, 592–603. [CrossRef]
10. Florita, A.; Hodge, B.-M.; Orwig, K. Identifying Wind and Solar Ramping Events. In Proceedings of the 2013 IEEE Green Technologies Conference (GreenTech), Denver, Colorado, 4–5 April 2013; IEEE: Piscataway, NJ, USA, 2013; pp. 147–152.
11. Saikumar, K. (2020). RajeshV. Coronary blockage of artery for Heart diagnosis with DT Artificial Intelligence Algorithm. Int J Res Pharma Sci, 11(1), 471-479.
12. Saikumar, K., Rajesh, V. (2020). A novel implementation heart diagnosis system based on random forest machine learning technique International Journal of Pharmaceutical Research 12, pp. 3904-3916.