



Operation and Control Strategies of Integrated Cross Grid Energy Resources Using Moa Algorithm

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ABSTRACT: With the recent developments in distribution of power generation with micro grids and smart grid technology, the evolution has moved towards integrating the distributed generation and micro grids. There are several meta-heuristic optimization techniques available under different categories. One of the most difficult tasks in forecasting and cost minimization of micro-grid is to select the best suitable optimization technique. To resolve the problem of selecting a suitable optimization technique, a rigorous review of different meta-heuristic algorithms is conducted and proposed a smart micro-grid (SMG) operation cost minimization problem. A proposed SMG is modeled which incorporates utility connected power resources, e.g., wind turbine, photovoltaic, fuel cell, micro-turbine, battery storage, electric vehicle technology, and diesel power generator. Load forecasting is the foundation for distribution systems planning because load growth is the main trigger for grid expansion. Conventional load forecasting focused on the amount of load growth. The goal of spatial load forecasting is to estimate with reasonable accuracy, and a high level of geographic resolution, not only the amount of load growth, but also when and where new load will occur. This information is then used to determine the best locations for distribution facilities and to plan system growth (e.g., new substations, distribution feeders, transformers, and so on). Spatial load forecasting is performed on the basis of small areas, historical load and weather data, land use, and geographic information. Comparative analysis of these methods is also done in this survey. Furthermore, the forecasting techniques are reviewed from the aspects of big data and conventional data by using Meta-heuristic Algorithm.

KEYWORDS: SMG, Metaheuristics Optimization Algorithm, Big data and Forecasting

I. INTRODUCTION

The data analytics based renewable energy forecasting methods are a hot research topic for a better regulation and dispatch planning in such cases. Traditional electricity meters in distribution systems only produce a small amount of data which can be manually collected and analyzed for billing purpose. While the huge volume of data collected from two-way communication smart grids at different time resolutions in nowadays need advanced data analytics to extract valuable information not only for billing information but also the status of the electricity network. For example, the high-resolution user consumption data can also be used for customer behavior analysis, demand forecasting and



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energy generation optimization. Predictive maintenance and fault detection based on the data analytics with advanced metering infrastructure are more crucial to the security of power system. Thus, C. Nagarajan et al [2,4,6] has studied the great progress of information and communication technology (ICT) provides a new vision for engineers to perceive and control the traditional electrical system and makes it smart. An embedded information layer into the energy network produces huge volume of data, including measurements and control instructions in the grid for collection, transmission, storage and analysis in a fast and comprehensive way. It also brings a lot of opportunities and challenges to the data analysis platform.

To resolve the problem of selecting a suitable optimization technique, a rigorous review of different meta-heuristic algorithms is conducted and proposed a smart micro-grid (SMG) operation cost minimization problem. A proposed SMG is modeled which incorporates utility connected power resources, e.g., wind turbine, photovoltaic, fuel cell, micro-turbine, battery storage, electric vehicle technology, and diesel power generator. The proposed work will help researchers and engineers to select an appropriate optimization method to solve micro-grid optimization problems with constraints. This system provides a detailed review of micro-grid operation cost minimization techniques. Load forecasting is the foundation for distribution systems planning because load growth is the main trigger for grid expansion. Conventional load forecasting focused on the amount of load growth. The goal of spatial load forecasting is to estimate with reasonable accuracy, and a high level of geographic resolution, not only the amount of load growth, but also when and where new load will occur. This information is then used to determine the best locations for distribution facilities and to plan system growth (e.g., new substations, distribution feeders, transformers, and so on). Spatial load forecasting is performed on the basis of small areas, historical load and weather data, land use, and geographic information. Comparative analysis of these methods is also done in this survey. Furthermore, the forecasting techniques are reviewed from the aspects of big data and conventional data by using Meta-heuristic Algorithm.

II. EMISSION LOAD DISPATCH

In environmental dispatch, additional considerations concerning reduction of pollution further complicate the power dispatch problem. The basic constraints of the economic dispatch problem remain in place but the model is optimized to minimize pollutant emission in addition to minimizing fuel costs and total power loss. Due to the added complexity, a number of algorithms have been employed to optimize this environmental/economic dispatch problem. Notably, a modified bee's algorithm implementing chaotic modeling principles was successfully applied not only in silicon, but also on a physical model system of generators.

Another notable algorithm combination is used in a real-time emissions tool called locational emissions estimation methodology (LEEM) that links electric power consumption and the resulting pollutant emissions. The leem estimates changes in emissions associated with incremental changes in power demand derived from the locational marginal price (LMP) information from the independent system operators (ISOS) and emissions data from the us environmental protection agency (EPA). LEEM was developed at Wayne state university as part of a project aimed at optimizing water transmission systems in Detroit, mi starting in 2010 and has since found a wider application as a load profile management tool that can help reduce generation costs and emissions.

Thermal power stations are major causes of atmospheric pollution, because of high concentration of pollutants they cause. It is utmost important to protect our environment from harmful emissions out from thermal power plants. Power utilities using fossil fuels as a primary energy source, give rise to particulates and gaseous pollutants apart from heat. The particulates as also the gaseous pollutants such as carbon dioxide (CO₂), oxides of sulphur (SO₂) and oxides of nitrogen (NO₂) cause detrimental effects of CO₂ on the environment is not yet precisely known. Pollution control agencies (Municipal/Governmental regulatory bodies) restrict the amount of emission of pollutants depending upon



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their relative harmfulness to human beings .So, the emission dispatch has been formulated. Of the pollutants emitted, NO_x is of major concern and hence it has been considered. The objective of emission dispatch is to minimize the total environmental degradation or the total pollution emission due to burning of fuels for production to meet the load demand. Hence, there is a need to formulate the combined emission and economic dispatch (CEED) problem. The idea behind combined emission and economic dispatch is to compute the optimal generation for individual units of the power system by minimizing the fuel cost and emission levels simultaneously.

The amount of emission from a fossil-based generating unit depends on the amount of power generated by that unit. The total emission level E from all the units in the system can be expressed as,

$$E = f_2(P_G) = \sum_{t=1}^N (0.5\alpha_t P_G^2 + \beta_t P_G + \gamma_t) \text{ lb/h} \quad (3.8)$$

Where, $\alpha_t, \beta_t, \gamma_t$ are the emission curve coefficients of the *i*th generation unit.

III. METAHEURISTIC - ALGORITHM

Metaheuristic is a higher level procedure or heuristic designed to find, generate, or select a heuristic (partial search algorithm) that may provide a sufficiently good solution to an optimization problem, especially with incomplete or imperfect information or limited computation capacity.

These are properties that characterize most metaheuristics:

- Metaheuristics are strategies that guide the search process.
- The goal is to efficiently explore the search space in order to find near-optimal solutions.
- Techniques which constitute metaheuristic algorithms range from simple local search procedures to complex learning processes.
- Metaheuristic algorithms are approximate and usually non-deterministic.
- Metaheuristics are not problem-specific.

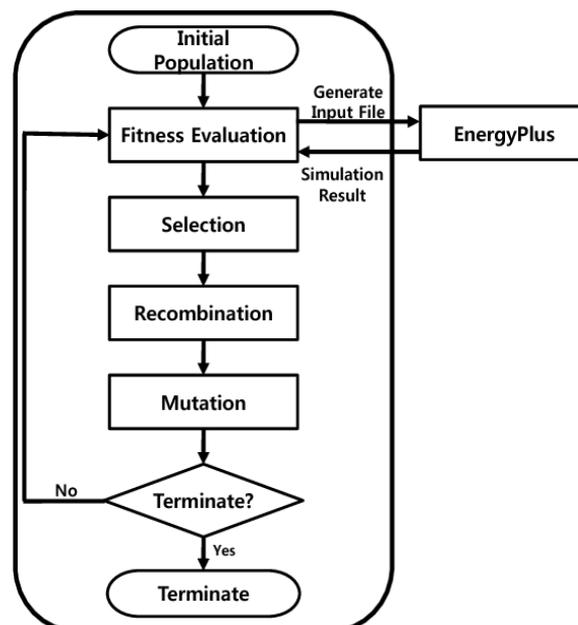


Fig: 3.1 Flowchart- Metaheuristic Algorithm



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a. Cost Function

The primary objective of the ELD problem is to minimize the cost function and determine the most economic loadings of the generators such that the load demand in a power system can be met. It can be described as an optimization process with the following objective function and equality and inequality constraints.

$$C = \sum_{i=1}^N C(i) \$/h \quad (3.1)$$

Where, $C(i)$ -cost function

The generated real power P_{Gi} account for the major influence on C_i . The Individual real generation are raised by increasing the prime mover torque, and this requires a cost of increased expenditure of fuel. The reactive generations Q_{Gi} do not have any measurable influence on C_i because they are controlled by controlling by field current. The individual production cost C_i of generator unit I is therefore for all practical purposes a function only of P_{Gi} , and for the overall controllable production cost, we thus have

$$C = \sum_{i=1}^N C(i)P_G(i) \quad (3.2)$$

Where, C =cost function, $C(i)$ =individual production cost, $P_G(i)$ =power generation, Where the cost function C can be written as a sum of terms where each term depends only upon one independent variable.

b. Equality Constraints

From observation we can conclude that cost function is not affected by the reactive power demand. So the full attention is given to the real power balance in reactive power demand. So the full attention is given to the real power balance in the system. Power balance requires that the controlled generation variables P_i obey the constraints equation.

$$P_d = \sum_{i=1}^N C(i)P_G(i) \quad (3.3)$$

Where, P_d -power demand

3.1 Functional Block of the System

The system consists of Power source, smart meter, Data Base management system and Load. The electrical power consumed by the power source by each individual building or industry connected from the main grid is measured using the smart energy meters. The readings of power consumption are made on the smart meter units is based on the number of loads connected and the time for which the load consumes power. These data of smart meter are managed in the data base or data store for further processing.



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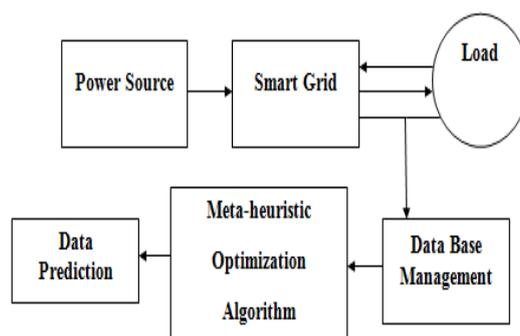


Fig: 3.1 functional block diagram of the proposed system

The data collected from the meters are if huge amount of data that has to be managed and processed efficiently. The large amount of data can be classified and processed using a classifier with predictive machine learning algorithm called Support Vector Machine. Machine learning is a multi-disciplinary field, involving many disciplines such as probability theory, statistics, approximation theory, convex analysis, and algorithm complexity theory. Specializing in how computers simulate or realize human learning behavior to acquire new knowledge or skills, and reorganize existing knowledge structures to continuously improve their performance. The machine learning is applied to the calculation and classification of data acquired from the smart meters. Repeated learning through the machine improves the accuracy of calculations. Based on the learning set results of the data processed the algorithm provides the prediction data for the smart metering system.

IV. EXPERIMENTAL RESULTS

The Experiments are conducted and simulated using the .Net framework and big data analysis is made with the data collection and management using access database. The experimental view and grid parameters and results are provided below:



Fig: 5.1 Complete Design Window



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Fig: 5.2 Energy calculations for Different Grid loads with time

Table 5.1 : PV Panel specifications

Parameter	Value
Maximum power (P_m)	8044 W
Open circuit voltage (V_{oc})	406 V
Voltage at P_m (V_{amp})	336 V
Short circuit current (I_{sc})	28 A
Current at P_m (I_{amp})	23.9 A
Temp coefficient for P_m	- 0.46 (%/ $^{\circ}$ C)
Temp coefficient for V_{oc}	- 0.129(%/ $^{\circ}$ C)
Temp coefficient for I_{sc}	0.052 (%/ $^{\circ}$ C)
No. of cells & connections	11 in series

Table 5.2: Generator data

Parameter	Value
Rotor type	Round
Number of Phases	3
Base E.M.F	Sinusoidal
Flux Linkage	0.433
Stator resistance	0.425 ohms
Stator inductance	0.000395 H
Rotor resistance	0.00702(p.u)
Rotor inductance	0.05051(p.u)
Inertia constant	0.01197 s
Friction factor	0.001189 p.u
Pairs of poles	5



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Table 5.3: Turbine Data

Parameter	Value
Base wind speed (wbase)	12 m/s
Maximum power at wbase (k_p)	0.8 p.u
Coefficient (c1-c6)	[0.5176, 116, 0.4, 5, 21, 0.0068]
Nominal performance coefficient	8500.00
Base rotational speed	1 p.u
Wind Power	3155 W

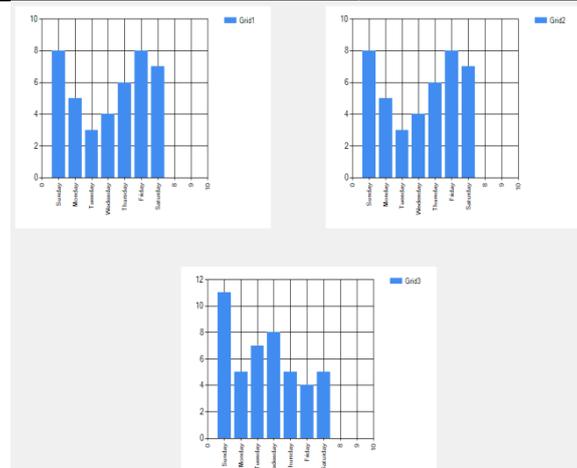


Fig: 5.3 Grid Load Estimation on daily basis

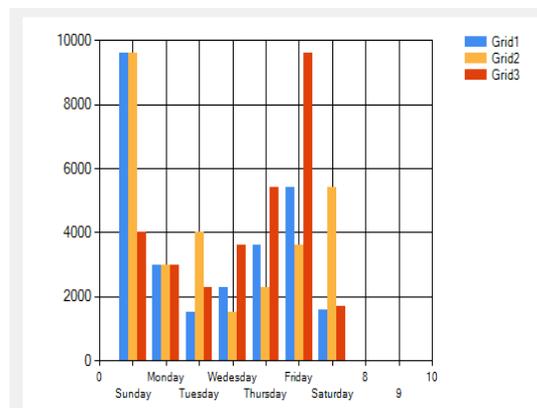


Fig: 5.4 Cost Estimation and comparison of different grids

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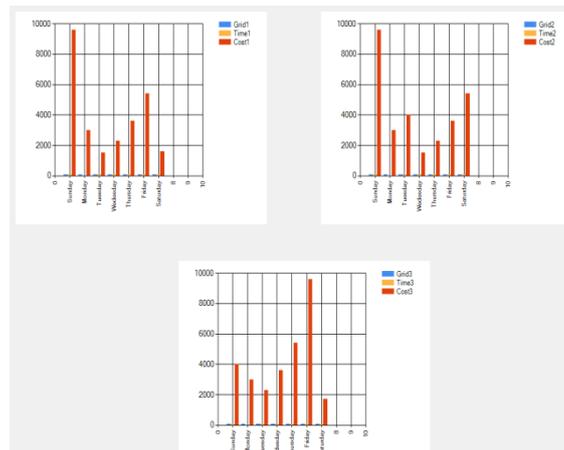


Fig: 5.5 Overall Grid Load and cost Analysis of three grids

The generator speed (rpm) and the generator power (p.u.) characteristics for the WT model are shown in Fig. 5.6 corresponding to various wind speed values. The output power of WT depends on the wind speed and generator speed. As depicted in Fig, wind speed is the most influential factor on the amount of power produced by the wind turbine. Because the power in the wind is a cubic function of wind speed, changes in speed produce a profound effect on power.

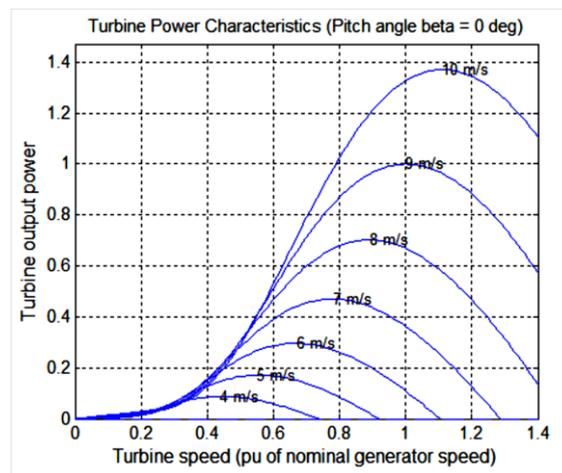


Fig. 5.6 Wind turbine characteristics

VI. CONCLUSION

Optimization algorithms are an important tool in the search for technical solutions and financial improvements in different scenarios and integration processes of distributed generation into current electric networks and smart grids. Therefore, scientists are recommended to proceed with these developments in order to make these technologies more accessible for all users and promote the efficient use of energy. Further, the multi task learning framework provides superior forecasting performance in terms of four important criteria compared with several popular benchmark



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methods. The proposed approach is very suitable for practical applications such as residential demand response and network reliability analysis in smart grids.

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