Statistical Analysis of Hybrid Renewable Energy Systems by using Artificial Intelligence

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Abstract

Hybrid renewable energy sources do not have consistent output capabilities, due to which a combination of these sources is used for real time usage. For instance, solar panels can provide good energy outputs during sunny days, but the output declines during windy weather. But during windy weather, windmill-based power sources can be used to compensate for energy gaps. Similarly, during rains the hydro-electric pumps are activated in order to produce better power outputs. In order to design such a hybrid system, vast variety of system models have been proposed by researchers. Each of these system models have then own nuances, advantages, and limitations; which makes it difficult for engineers to adopt a particular model for their given deployment. Renewable energy system deployment engineers need to do a lot of testing, validation and parametric estimation in order to evaluate the best combination of control strategies for their systems; which increases deployment time and cost. In order to cut the cost and time of deployment, this text reviews some of the most optimum control strategies, and compares them in terms of parameters like accuracy of control, response time, etc. w.r.t. the scale of deployment. This text would assist system designers to select the most optimum control models for improving the efficiency of hybrid renewable power systems. Moreover, this text also recommends methods to improve the efficiency of the reviewed control models, thereby improving their applicability for real time deployments.

Keywords: Hybrid, energy, control, machine, learning, deployment, solar, wind, hydroelectric.

I. Introduction

Renewable energy and its efficient consumption are need of the hour for catering power demands of the ever-increasing human population. It is estimated [1] that use of renewable energy reduces electricity bills by 30%, adds over 90k jobs every year, and reduces overall carbon footprint by over 25% when compared to non-renewable resource consumption. Renewable energy Sources include Solar power, Wind power, and Hydro power, which can be combined in order generate massive amount of electrical power for day-to-day consumption. The main issue with these sources is their inconsistency, due to which, various device control and power storage systems are designed. These systems perform the following tasks in order to improve the efficiency of storage & consumption of electricity from these hybrid sources,

- Prediction of control parameters like Solar panel movement, activation of wind power systems, controlling flow of hydroelectric power, etc.
- Filtering of generated power, and its storage for future usage.
- Estimation of load balancing for improving the overall power efficiency of the hybrid model.
- Reduction in losses due to static placement of hybrid power generators, thereby further enhancing power production capabilities.

Sample architecture for such a hybrid control unit can have photo voltaic (PV) cells, wind turbines, bio gas and hydroelectric power control systems are deployed.

The system initializes by analysing power from PV and Wind turbines, and activating an inverter module. The module converts this power into alternating current (AC), and passes it to the control unit, where filtering and storage operations are performed. Power from hydroelectric generator is given to a generating motor, wherein it is converted into AC and fed to control unit. Finally, a biogas generator also converts power from direct current (DC) into AC and feeds it into the control unit. Combination of all these power sources is controlled by a central control unit, from where it is finally given to the load (household or grid). A wide variety of control systems are proposed by researchers and system designers over the past years. Survey of these control systems, and their nuances can be observed from the next section. This is followed by an experimental analysis of these models in terms of accuracy of control and response time under different scenarios. Finally, this text concludes with some interesting observations about the reviewed models, and recommends methods to further improve their performance.

II. Literature Review

Control system design for hybrid renewable energy sources is a multidomain task, which involves signal processing, filter design, inverter design, battery charge/discharge cycle design, etc. A wide variety of source specific control system designs have been proposed by researchers, which aim at improving power storage and utilization capacity from specific renewable sources. For instance, the work in [2] proposes a terms of use (TOU) algorithm for improving efficiency of photovoltaic power systems that use diesel generators as backup. The proposed model is able to reduce energy wastage by 20%, and reduce cost of consumption by over 15% when compared with general purpose diesel-solar generation systems. The system model uses FMINCON algorithm which is based on 2nd order Lagrangian derivatives for obtaining optimum solar panel performance. A similar system that uses solar power to solve load shedding issues can be observed in [3], wherein Mixed Integer Programming is used to solve Multiple Knapsack Problem. The fair load shedding problem (FLSP) solved in this work is tested on over 8 datasets, with varying locations and data points of analysis. Consumption of various devices is tracked, which assists in deciding daily average consumption per device, and weekly consumption per device. Using this data, a Mixed Integer Programming based Multiple Knapsack Problem is solved using Genetic Algorithm (GA), comfort model (CM), supply model (SM) and crow search algorithm (CSA). The GA model performs better than CSA model in terms of power generation capabilities, wherein GA model has a power loss of 10.75%, while CSA has a power loss of 13.9% on various datasets. This performance can be further extended using particle swarm optimization (PSO) as discussed in [4].It can be observed that PSO models have superior optimization performance and can be used to boost the microgrid performance via power loss reduction by 18% when compared to non-PSO based systems. This performance is achieved under hybrid microgrid conditions, thereby making it applicable for a wider number of applications. Similarly, the work in [5] proposes use of classic optimization models like Linear Programming (LP), Mixed Integer LP, and model that use iterative & analytical methods. This text also reviews performance of various Genetic Algorithms, artificial bee colony (ABC) optimization, PSO models, ant colony optimization (ACO) models, Preference-inspired co-evolutionary algorithm (PICEA), fruit fly optimization (FFO) algorithm, Artificial bee swarm optimization (ABSO), Biogeography-based optimization (BBO), Harmony search (HS) optimization, and Imperial competitive algorithm (ICA) for optimizing design of hybrid renewable system models. The work further states that a combination of linear and bio-inspired models like Hybrid teaching–Learning-Based Optimization algorithm (HTLBO), Modified Electric System Cascade Analysis (MESCA), Hybrid Simulated Annealing-Tabu Search Algorithm (HSATSA), Discrete Chaotic HS-based Simulated Annealing algorithm (DCHASSA), Hybrid Flower Pollination Algorithm and Simulated Annealing (HFPASA), Improved Simulated Annealing Particle Swarm Optimization (ISAPSO), etc. outperform individual models, because coarse grained analysis is done by the conventional models, while fine grained analysis is performed by the bioinspired models; which assists in enhancing overall system stability. An application of these models can be observed in [6], wherein Wind energy systems (WTG), small hydropower plants, Biogas plants, Solar photovoltaic (PV) systems, and Geothermal devices & heat pumps are controlled via hybrid bioinspired Electrical Transient Analyzer Program (ETAP).

The model is capable of reducing power losses by over 15% when compared with conventional systems, and has good speed of operation. It is also able to reduce number of drops in power, thereby assisting in an improved control system design for renewable power generation. This efficiency can be further improved via the use of stochastic optimal load aggregation (SOLA) [7], which utilizes a randomized model for estimation of loads, thereby assisting in improving the power efficiency. The model reduces peak-to-average-power ratio (PAPR) by 8% when compared to non-stochastic modelling, thereby reducing generation costs, and standard deviation of generated power. A similar TOU-based system that utilizes load shifting (LS), with scheduled load reduction (SLR) is proposed in [8], wherein energy consumption is reduced by 5%, power loss is reduced by 20%, and power factor is improved by 19% for LS, while energy consumption is reduced by 19%, power loss is reduced by 49%, and power factor is improved by 24% for SLR systems when compared with non-LS and non-SLR models respectively. This performance can be further improved by the use of GA based modelling as proposed in [9], wherein optimum utilization of PV, wind turbines, and battery systems is done.

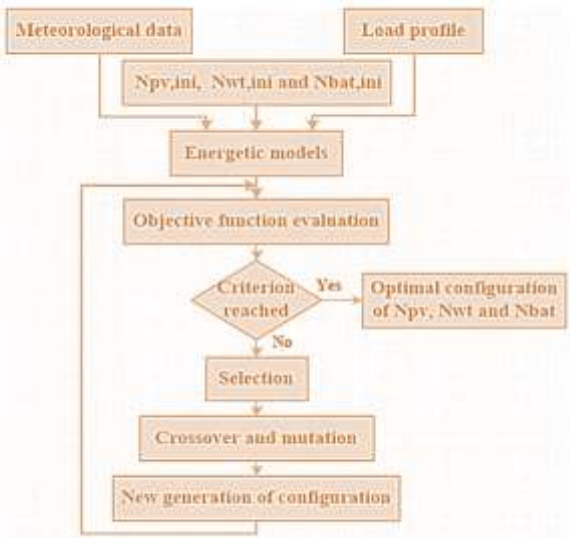

Fig. 1 GA model for hybrid renewable power systems [9]

The flow of this model can be observed from Fig. 1, wherein meteorological data and load profiles are scanned, and given to energy optimization model along with initial values of PV, wind and battery power.

This method uses energy deficit, and life cycle costs (LCC) in order to model the fitness function, which is optimized via minimization. The model is able to reduce power losses by 4.62%, and improve power factor by 8% when compared with a system model that doesn't use Genetic Algorithm. This performance can be further improved via the use of hybrid heuristic models as observed in [10], wherein Salp Swarm Algorithm (SSA), Whale Optimization Algorithm (WOA), Grey Wolf optimizer (GWO), and Water Cycle Algorithm (WCA) are used for inter algorithm validation. It is observed that WOA outperforms all other algorithms by reducing the power loss by 18%, while GWO reduces this by 8%, SSA by 12% and WCA by 9%, thereby improving the deployment capabilities of WOA for real time hybrid power generation systems. Similar to this, a highly efficient joint estimation based solar generation model that uses mixed hidden Markov model (MHMM) is described in [11], the model showcases 67% reduction in error when compared with non MHMM systems. From a power loss perspective, the MHMM outperforms HMM by 8%, consumer mixture model (CMM) by 14%, and 18% by unsupervised disaggregation models. This efficiency can be further improved via estimating battery impact on commercial voltage profiles (CVP) as suggested in [12], wherein factors like TOU, and maximum demand (MD) are considered. Due to addition of battery impact analysis, the model is able to reduce consumption costs by 14% when compared with systems that do not perform battery impact analysis. Applications of these systems can be observed from [13], [14] where home load management system designs for India and its neighbouring countries is estimated using various technical and economic analysis.

Solar panels can also be integrated with uninterrupted power systems (UPS) for improving their storage performance. The work in [15] proposes design of such a system, wherein a solar integrator is used with UPS, wherein the integrator uses a combination of AC/DC and DC/DC converters with maximum power point tracking (MPPT) for storing battery charges. It is observed that this combination assists in reducing power loss by 14% when compared with standalone UPS models. A similar system model is proposed in [16], wherein techno economic analysis is performed to optimize performance of PV batter systems. The system uses pulse-width modulation with partial integral (PI) control in order to generate gating pulses for the solar panel. The proposed model with 4 DC/DC load converters, and central controller design is use of bi-directional DC/DC converters for controlling Lithium Ion (Li) battery charging/discharging cycles, and unidirectional DC-DC converter for PV conversion are seen.

The proposed model is able to reduce power loss by 8% when compared with standalone battery systems, and thus can used for household applications. Efficiency of this model can be further improved via improved controller design using clustering, and optimization algorithms. The work in [17] proposes such an algorithm, wherein prosumer microgrids (PMGs) are analyzed using kMeans &kMedoids clustering, while sizing of devices is controlled using differential evolution algorithm (DEA). The model is able to reduce power losses by 9%, and is applicable for small scale power distribution systems. To further improve this performance, a fog based microgrid control system for managing hybrid power sources is described in [18]. The proposed model is applied for power optimization of micro data centres in rural areas, but can be extended for other geographies. The model showcases a power loss reduction of 14% due to use of PSO & software defined networking (SDN) based hybrid green power source sizing. An extension to this work can be observed from [19], wherein renewable-storage energy system design for mixed power usage is proposed. It uses hybrid optimization model for electric renewables (HOMER) for reducing power loss by 15% when compared with standard implementation.

Use of machine learning based power pattern analysis system models like neural networks (NNs) can also be done for improving power control. Work in [20] proposes such a system model that uses a modified neural network design for estimation of reference current in order to control the pulses produced for controlling Insulated Gate Bipolar Transistor (IGBTs) used in Voltage Source Converters (VSCs). Due to this control, the model is able to reduce power losses by 18%, and improve accuracy of decision making by 8% when compared with a non-neural network model. This efficiency can be improved via use of Persistent Extreme Learning Machine (PELM) as proposed in [21], wherein different renewable energy sources are combined in order to improve overall efficiency of power control model. The model is able to reduce power losses by 8%, and increase efficiency of conversion by 14% when compared with non-PELM model. This performance can be improved by modifying HOMER to work with PELM model for producing highly accurate and sensitive results. Such a modified HOMER model is proposed in [22], which provides an energy efficiency of 22%, with a power loss reduction of 19% when compared with standard implementations. But delay response of HOMER model is limited, due to which the work in [23] proposes a model for demand side load control using multiagent systems with antlion optimization. This system is capable of achieving energy efficiency of 18%, and power loss reduction of 15%, but is 27% faster than state-of-the-art control models. Another high-speed model for control of hybrid power systems can be observed from [24], wherein differential evolution (DE) is used. The proposed DE model internally uses modified fuzzy non-Pareto based multiple objective solvers, that assists in interfacing multiple power sources for performance optimization. It is observed that the proposed model has high efficiency of conversion, and showcases power loss reduction by 16% when compared with standard implementations.

PV systems capture over 70% of all renewable energy sources, due to which their control systems are most widely researched. The work in [25], [26] proposes design of such PV control systems using power profile analysis, and achieve energy efficiency of 8%, with a power loss reduction of 13% when compared without power profile analysis. An interesting piece of research done in [27] proposes use of energy rate (ER), carbon dioxide emission reduction (CER), and total operation cost (TOC) for combined cooling heating and power system (CCHP) design. Design of a standard CCHP system can be used for cooling load, heating load, and electricity load, is controlled using natural gas infusion and exhaustion. Due to use of ER, CER and TOC the model is able to reduce power generation loss by 19%, and improve efficiency of energy conversion by 8% when compared with individual control systems. This makes the system applicable to a wide variety of real time power system deployments as observed in [28]. This efficiency can be further improved via use of hybrid control mechanisms as proposed in [29], wherein ACO and cuckoo search (CS) are combined. The model is able to reduce energy losses by 15%, and improve efficiency of generation by 16% when compared with standalone algorithms. Efficiency of renewable energy control models can also be used for energy co-ordination, the work in [30] proposes such a model wherein dynamic distributed energy storage strategy (DDESS) is proposed. The model is able to optimally design energy co-ordination between different energy sources, thereby improving overall efficiency of power distribution, and reducing power losses by 8%, and improving energy conversion by 14%, while maintaining high conversion speeds.

Pricing of smart hybrid renewable system models can be optimized using the work in [31], while demand responses can be controlled via minimization of critical excess electricity production (CEEP) as proposed in [32], wherein variable renewable energy sources (VRES) are controlled using

Energy Plan model. Similar models are used in [33]–[35], where HOMER, fuzzy inference system (FIS) with PSO, and combination of dynamic voltage restorer (DVR), distribution static compensator (DSTATCOM), and unified PQ conditioner (UPQC) are used. Thereby suggesting that hybrid combination of machine learning and signal processed models must be used for efficient power control analysis for hybrid renewable power systems. This will assist system designers to select the best combination of models for their given hybrid renewable energy system deployment.

III. Empirical analysis of control strategies for hybrid renewable energy systems

A wide variety of algorithms have been reviewed for design of control systems to achieve high efficiency of conversion with minimum loss during renewable energy system design. In order to compare their individual performance, this section compares them on the basis of power loss reduction, efficiency of conversion, response time, computational complexity, and applicability. This comparison will assist system designers to select the most useful algorithms for their deployments. Due to unavailability of standard values for these metrics, this section converts each of these metric values into low (L), medium (M), high (H), and very high (VH) ranges by considering performance of a non-optimized hybrid renewable system model proposed in [2]. Using this method, fuzzy parametric values for power loss reduction (P), efficiency of conversion (E), response time (T), computational complexity (C), and application of use (A).

From this analysis, it can be observed that majority of systems designed for controlling power flow in renewable energy systems are developed for either PV (solar) or general (hybrid) energy sources. Thus, analysis of these models for power loss reduction, efficiency of conversion, response time, and computational complexity can be done on the basis of solar and hybrid applications. After reviewing this analysis, researchers will be able to identify best performing models for their given application. For instance, the power loss reduction performance for different models, wherein it can be observed that ABSO [5], ACO with CS [29], and WOA [10] outperform other models.

The efficiency of conversion for different models, wherein it can be observed that, Multiple agents with antlion [23], ABC [5], and WOA [10] outperform other models. The response time for different models, wherein it can be observed that, Multiple agents with antlion [23], ABC [5], and DEA with kMeans [17] outperform other models. The computational complexity for different models, wherein it can be observed that, FFO [5], GA with LCC [9], and GWO [10] outperform other models. Based on these parameters, a total performance parameter (TP) was evaluated using equation 1, wherein conversion efficiency (E), power loss reduction (P), response time (T), and computational complexity (C) are combined.

$$\mathrm{TP} = \frac{E+P}{T+C} \tag{1}$$

This parameter is evaluated for all hybrid energy systems, and its performance is observed that FFO [5], GA with LCC [9], and WCA [10] outperform other algorithms.

The evaluation is done for PV systems, for instance, indicates the power loss reduction performance for different models, wherein it can be observed that TOU with PV and diesel generator [2], and PELM [21] outperform other models. The efficiency of conversion for different models, wherein it can be observed that, PELM [21], and NN [20] outperform other models. The computational complexity for different models, wherein it can be observed that, LS [8], and DDESS

[30] outperform other models. The total performance for different models, wherein it can be observed that, LS [8], SLR [8], and MHMM [11] outperform other models.

Thus, from this in-depth analysis it can be observed that machine learning and hybrid soft computing models outperform other models in terms of power loss reduction, efficiency of conversion, response time, and computational complexity for both hybrid renewable power systems, and PV power systems.

IV. Conclusion and future scope

Analysis of different models for control of hybrid renewable energy systems, and PV systems in terms of power loss reduction, efficiency of conversion, response time, and computational complexity indicate that combination of various soft computing techniques, and linear programming models showcase better performance than conventional models. From an application viewpoint, it can be observed that ABSO [5], ACO with CS [31][29], CVP with TOU [12], DCHASSA [5], DVR, DSTAT-COM, UPQC [35], ER, CER, TOC [27], FFO [5], FLSP with GA [3], GA [5], GA with LCC [9], HOMER [19], HOMER [33], HSATSA [5], HTLBO [5], MESCA[5], Multiple agents with antlion [23], PICEA [5], PSO [4], WCA [10], WOA [10] outperform other models in terms of power loss reduction for hybrid renewable power systems, while TOU with PV and diesel generator [2], MPPT for UPS [15], Hybrid HOMER [22], and PELM [21] outperform other models in case of PV systems. Similarly, Multiple agents with antlion [23], ABC [5], ACO with CS [29], CVP with TOU [12], DCHASSA [5], FFO [5], FIS with PSO [34], GA with LCC [9], HFPASA [5], HOMER [33], HTLBO [5], ICA [5], MESCA [5], PSO [4], WOA [10] outperform other models in terms of efficiency of conversion for hybrid energy systems, while PELM [21], Hybrid HOMER [22], SLR [8], and NN [20] outperform other models for PV systems. It is also observed that response time in case of hybrid renewable power systems is better when Multiple agents with antlion [23], ABC [5], FFO [5], GA with LCC [9], ICA [5], WOA [10], ABSO [5], BBO [5], ER, CER, TOC [27], LP[5] [5] PICEA [5], SOLA [7], WCA [10], or DEA with kMeans [17] are used, while in case of PV it is better when SLR [8], TOU with PV and diesel generator [2], MPPT for UPS [15], LS [8], MHMM [11], or CMM [11] are used. Similarly, in case of computational complexity for hybrid renewable systems, FFO [5], GA with LCC [9], PICEA [5], SOLA [7], CVP with TOU [12], PSO [4], ETAP [6], GWO [10] outperform other models, while, for PV systems, LS [8], SLR [8], TOU with PV and diesel generator [2], CMM [11], PI with MPPT [16], Power Profile Analysis [25], DDESS [30] outperform other models. A combined score indicates that FFO[5], GA with LCC [9], Multiple agents with antlion [23], PICEA [5], CVP with TOU [12], PSO [4], WOA [10], ABC [5], ABSO[5] , ER, CER, TOC [27], ICA [5], and WCA [10] outperform other algorithms for hybrid models, while LS [8], SLR [8], TOU with PV and diesel generator [2], MPPT for UPS [15], PELM [21], PI with MPPT [16], Power Profile Analysis [25], MHMM [11] outperform other models for PV systems. It is further recommended that, deep learning models with reinforcement learning must be used in order to improve efficiency of this model, and validate it using real time implementation.

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