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Article

Intelligent ANFIS-controlled solar PV energy management system with GTO-based multi-agent optimization for smart grid applications

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Abstract: A solar power plant is a large-scale facility that converts sunlight into electricity using photovoltaic (PV) panels or to supply renewable energy to the grid or commercial users. The proposed solution offers a solar power plant's intelligent energy management framework along with cutting-edge optimization methods and hybrid energy sources. Using an Adaptive Neuro-Fuzzy Inference System (ANFIS) controller, the architecture integrates a solar PV module, utility grid supply, and battery storage. By managing solar irradiance uncertainty and dynamic demand situations, the ANFIS controller effectively controls power flow between generating, storage, and load components. To guarantee steady functioning and longer battery life, a charger subsystem controls battery charging and discharging. Additionally, a Multi-Agent System (MAS) based on Group Teaching Optimization (GTO) is used to optimize energy distribution among various loads, including EVs, drones, and portable gadgets, enhancing overall system dependability and efficiency. In contemporary smart grid contexts, the combination of intelligent control and metaheuristic optimization improves energy efficiency, reduces reliance on grid power, and promotes sustainable and autonomous energy management.

Keywords: solar PV, adaptive neuro-fuzzy inference system (ANFIS) controller, group teaching optimization, multi-agent system (MAS), energy, voltage

1. Introduction

One of the most promising forms of renewable energy in the upcoming generation is expected to be PV systems. These days, installed solar systems are getting cheaper due to a drop in the average selling price of components. Numerous large-scale solar power plants have been connected to the electrical grid in recent years [1]. Network operators are finding it more challenging to maintain grid reliability and stability as PV power facilities are increasingly integrated into electric grids [2]. These devices are necessary to maintain the grid during blackouts, according to the utilities that have made medium voltage grid codes available to photovoltaic projects. Postfault voltage settings are frequently not possible with linear controllers due to their limited operating range. The power system model's nonlinearities make it difficult to achieve LVRT capabilities [3,4]. Both during and after faults, a system's state may diverge significantly from the anticipated equilibrium position. The majority of postfault uncontrolled systems have an unstable postfault trajectory. One method for resolving the LVRT issue is global stabilizing controller design [5].

Contribution of this work

The following are the key phases of the suggested approach, for further information:

- Developed an integrated system combining solar PV, utility power, and battery storage to ensure continuous and reliable energy supply under varying environmental and load conditions.
- Implemented an ANFIS controller to dynamically regulate power flow, handle uncertainties in solar generation, and improve decision-making accuracy.
- Introduced a GTO MAS) for optimal energy allocation among multiple loads such as EVs, drones, and portable devices, enhancing overall efficiency.
- Achieved improved energy utilization, reduced grid dependency, and extended battery life through coordinated control and optimization, contributing to a more sustainable smart energy system.

The following explains how the document was established. The introduction is found in Section 1. Section 2 provides a description of the pertinent works. The suggested methods are presented in Section 3, the experimental data is shown in Section 4, and a conclusion and future research are presented in Section 5.

2. Literature review

Ahmad et al. [6] have proposed, the renewable energy systems such as solar, wind, and hydro have become increasingly important. While these systems have numerous benefits, like being sustainable and clean, their main drawback is that they are less efficient than fossil fuel-based energy systems.

Wang et al. [7] have introduced, the model is solved using the enhanced adaptive GAPSO hybrid technique. In comparison to the outcomes of the conventional optimization algorithm, the enhanced algorithm reduces the daily operation cost of the scheduling scheme from RMB 170 to RMB 150, increases the green power consumption rate from 83 % to 86 %, and increases the well cluster's daily production by 4.86 %. A PC with a 13th Gen Intel(R) Core (TM) i5-13500H CPU running at 2.60 GHz and 16 GB of RAM runs all simulations in MATLAB.

Ssekulima et al. [8] have suggested, a framework for stochastic optimization and thoroughly evaluates six metaheuristics: Particle Swarm Optimization (PSO), Differential Evolution (DE), and Genetic Algorithm (GA) for single-objective optimization, and Non-dominated Sorting Genetic Algorithm II (NSGA-II), Multi-Objective Evolutionary Algorithm based on Decomposition (MOEAD), and Generalized Differential Evolution 3 (GDE3) for multi-objective optimization. The goal of the multi-objective methods was to reduce the cost of energy production while increasing overall energy output.

Ssekulima et al. [9] have discussed, the efficiency of GA + PO was 98.7 %, whereas the efficiency of GA + IC was 98.8% with a settling time of 10.3 ms. Across temperature ranges of 22–38°C and irradiance ranges of 750–1000 W/m², the hybrid techniques continuously maintained enhanced tracking accuracy and decreased steady-state fluctuations. Zhu et al. [10] have reported, a hybrid models that use optimization algorithms like fruit-fly optimizer, satin bowerbird optimizer, and particle swarm optimizer. The combination of HGBoost and satin bowerbird optimizer is the best-performing hybrid model (R2 = 0.9907), showing improved accuracy and lower error rates.

3. Proposed system

A proposed intelligent solar power management system that combines the production, storage, and optimal distribution of renewable energy is shown in **Figure 1**. The main energy source is a solar PV module, with utility electricity acting as a backup. An ANFIS controller, which intelligently controls power flow based on changing factors like solar availability and load demand, is in charge of both sources. The system has a battery-connected charger unit that allows for effective energy storage and regulated charging and discharging to keep the system stable. Furthermore, a GTO-assisted MAS is integrated to maximize energy distribution among various end-use applications, including drones, electric cars, and portable electronics. This well-coordinated structure guarantees effective energy use, lessens dependency on traditional power sources, and improves the sustainability and dependability of the entire energy system.

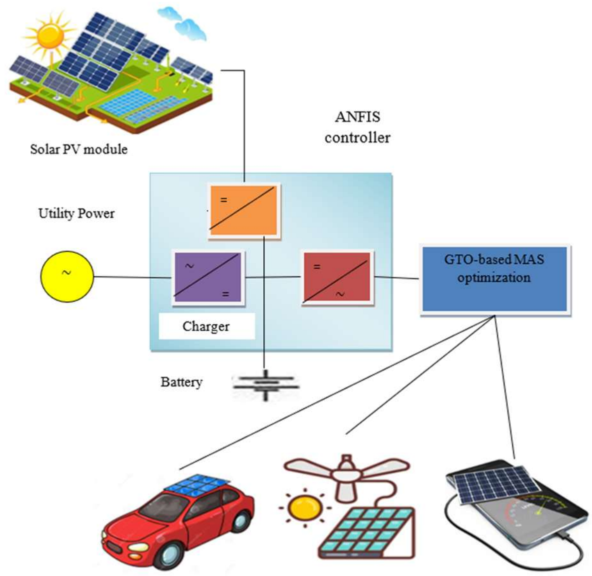


Figure 1. Block schematic for a solar power system that uses GTO-based MAS optimization management of energy.

3.1. Solar power plant

A solar thermal plant is a facility that uses a traditional thermodynamic cycle to transform sun energy into electricity. However, solar thermal power plants use a totally environmentally favorable energy source like sunshine, in contrast to thermal power plants that operate using conventional fuels. Depending on the type of solar thermal plant we are discussing, the technology utilized to generate power varies slightly, but the operating system is the same. In order to heat a fluid with thermally conductive qualities and raise its temperature until it turns into steam, a solar thermal power plant concentrates solar radiation. After that, a turbine receives it. Here, thermal energy is transformed into mechanical energy, which is then sent to an alternator for ultimate conversion into electricity. The solar power plant is shown in **Figure 2**.

Figure 2. Solar panels power plant.

3.2. Design of an ANFIS controller

One of the most popular methods for intelligent modeling and control is ANFIS. Fuzzy logic and neural network concepts are combined to create ANFIS. Using basic fuzzy inference, ANFIS can be utilized to build ANN-style intelligent systems that can reason and learn from experience. The neural fuzzy framework enhances the fuzzy rules developed by human specialists to categorize behavior based solely on input-output data.

The goal of the learning process is to change the properties of this fuzzy inference system. **Figure 3** illustrates the conventional configuration of an ANFIS controller, where a circle represents a fixed node and a square represents an adjustable component. The two inputs and one result to keep things simple.

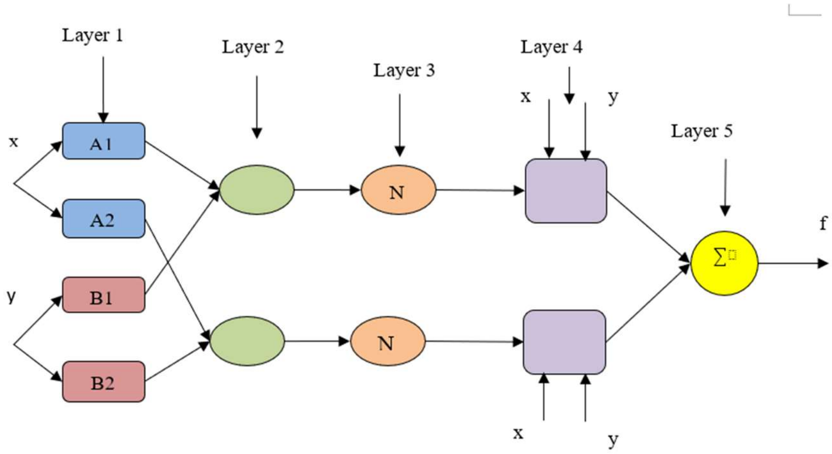


Figure 3. ANFIS architecture in its basic form.

The decision unit, database, basic rules, fuzzification interface, and defuzzification interface are its five main levels. The membership function assigned to each node in the first layer of the adaptive layer is as follows:

$$O_i^1 = \mu_{Bi}(x) \; for \; j = 1{,}2 \tag{1}$$

Where μ is the function value that encapsulates the membership of Bi, x is the input to the node *i*, and Ai is the language feature corresponding to this node function.

The total of all the messages received by every fixed, Γ-labeled component in the subsequent layer is its output.

Each node's output indicates a rule's weight, or firing power. The total of all the electrical impulses that enter each fixed, Γ-labeled node throughout the second layer is its output. Each node's output indicates a rule's weight, or firing power.

$$O_i^2 = W_i = \mu_{Bi}(x)\mu_{Ci}(y) for i = 1,2 \tag{2}$$

With the label *N*, every node in the subsequent tier is a continuous node. Constraints are known as normalized firing strength, or normalized weight.

$$O_i^3 = \overline{W_i} = \frac{W_i}{W_1 + W_2} for i = 1,2 \tag{3}$$

All of the nodes in the subsequent layer are adaptive, and their membership function is determined by:

$$O_i^4 = \overline{W_i} f_i = \overline{W_i}(s_i x + t_i y + u_i) for J = 1,2 \tag{4}$$

Where (s_i, t_i, u_i) is the node's subsequent parameter set and i w is a controlled discharge intensity from layer 3. The last layer's lone fixed node uses the following formula to sum all of the signals arriving and determine the output:

$$O_i^5 = \sum_i \overline{W_i} f_i = \frac{\sum_i W_i f_i}{\sum_i w_i} for J = 1,2 \tag{5}$$

3.3. Proposed GTO-enhanced MAS optimization for energy management

The MAS framework's optimization for hybrid power systems using different renewable energy sources is greatly improved with the addition of the GTO. The cooperation and foraging of gorilla groups, in which every member of the group works together to achieve a similar goal, like food or protection, serves as an inspiration for GTO. In energy systems with a large number of agents such as loads, energy storage devices, and renewable resources that cooperate to attain optimal performance, this group behavior is most appropriate for solving challenging optimization problems. The system can efficiently manage activities including dynamic resource allocation, energy dispatching, and balancing fluctuating energy loads when GTO and MAS are coupled. It imitates the lively behavior and social intelligence of gorillas in the wild. The two main stages of the GTO algorithm are exploration and exploitation, both of which are essential to system optimization and decision-making.

3.3.1. Exploration phase

The Three processes are used in the exploration step to improve the algorithm's capacity to thoroughly investigate the search space: Traveling to a known location, approaching other gorillas, and migrating to an unseen area. The algorithm can balance exploration and stay out of local optima thanks to these mechanisms. The following formulas determine the gorilla's position in iteration ($t+1$):

$$GX(t+1) = (UB - LB) \times r_1 + LB, \ rand < p, \tag{6}$$

$$GX(t+1) = (r_2 - C) \times X_r(t) + L \times H, \;\; rand \geq 0.5, \tag{7}$$

$$GX(t+1) = X(i) - L \times \left(L \times X(t) - GX_r(t)\right) + r_a \times (X(t) - GX_r(t)))rand < 0.5 \tag{8}$$

The supporting parameters are calculated as follows:

$$C = F \times (1 - \frac{It}{MaxIt}) \tag{9}$$

$$F = \cos(2 \times r_4) + 1 \tag{10}$$

$$L = C \times l \tag{11}$$

$$H = Z \times X(t) \tag{12}$$

$$Z = [-C, C] \tag{13}$$

3.3.2. Exploitation phase

By focusing on regions near high-quality solutions, the exploitation phase improves the search. In order to improve the quality of the solution, it mimics actions like dominance competition and silverback imitation (leader). The best solution discovered throughout each cycle is represented by the silverback. Based on the silverback's advice, gorillas modify their stances, which are mimicked by:

$$GX(t + 1 = L \times M \times (X(t) - X_{silverback}) + X(t) \tag{14}$$

where,

$$M = \left(\left|\frac{1}{N}\sum_{i=1}^{N} GX_i(t)\right|^g\right)^{\frac{1}{g}} \tag{15}$$

$$g = 2^L \tag{16}$$

This strategy introduces competition among gorillas, driving them to explore other potential solutions. It is mathematically represented as:

$$GX(i) = X_{\text{silverback}} - (X_{\text{silverback}} \times Q - X(t) \times Q) \times A \tag{17}$$

$$E = \begin{cases} N_1, & r \geq 0.5, \\ N_2, & r \geq 0.5, \end{cases} \tag{18}$$

The value of *C* is used to select the two method exploitations. The silverback method, which fills positions according to the direction of the silverback, is used whenever *C* is equal to or larger than *W*. The algorithm uses the approach of competition for adult females employing competitive interactions in an attempt to find even better solutions if *C* is less than *W.*

4. Results and discussion

The most widely used technical tool for engineers and scientists is

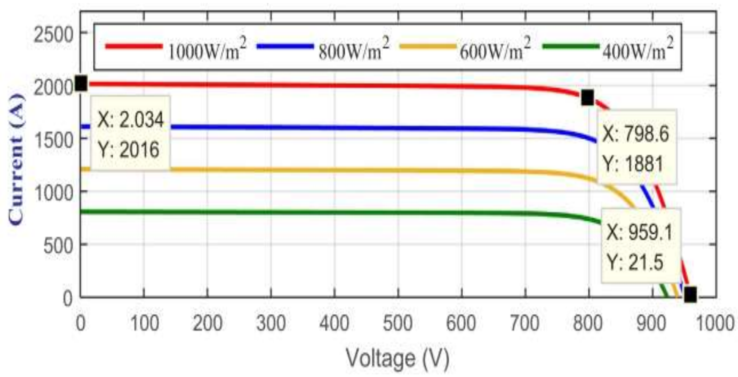
Matlab/SIMULINK, whose models have been validated by a number of technical activities and scientific papers. To validate the results, a number of simulations employing SIMULINK blocks will be constructed in this section of the article. A 100 kW two-stage solar array is connected to the grid via a 200 kVA three-level neutral point clamped voltage source inverter. A 150 kW dc-dc boost converter feeds it in series. The inverter's output voltage is 500 V, and its nominal frequency is 50 Hz. When the LC filter is connected to the inverter output, a distortion-free sinusoidal voltage waveform is produced. A grid's nominal voltage is 20 kV and its nominal frequency is 50 Hz. **Table 1** show the simulation parameter.

Table 1. Simulation parameter.

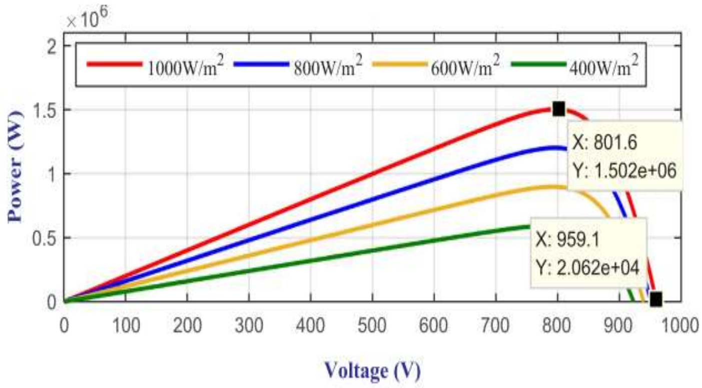
Block	Parameters	Typical values
Solar Input	Irradiance (G), Temperature (T)	200–1000 W/m², 25–45°C
PV Array Model	Voltage (V), Current (I), Power (P)	0–600 V, 0–10 A
Battery Storage	State of Charge (SOC), Voltage	SOC: 20–100%, 48–400 V
Charge Controller	Charging/Discharging Rate	0–100% rate
Inverter	Efficiency, Output Voltage	90–98%, 230 V AC
Load/Grid	Power Demand	1–10 kW
Performance Metrics	Efficiency, Power Output, Stability	Efficiency > 95 %

The array sizing calculation results are shown to be exactly the same as the simulation results, which are shown in **Figure 4**, using MATLAB/Simulink. Numerous tracking methods are employed to keep an eye on the PV array's peak performance. Due to its ease of use, practicality, and low sensor requirements, the perturb and observe (P&O) strategy is the most widely utilized of all the major MPPT techniques. In this work, the greatest power point (MPP) equivalent to temperature and radiation levels is followed using the P&O approach.

The 20 % voltage drop example has five search agents and thirty iterations. The simulation's convergence curve is shown in **Figure 5**, and the EWOA found that the objective function's most optimal value was 0.014546. After optimization, EWOA's best results are 40 and 3188.5158.



(a)



(b)

Figure 4. The PV system array's characteristic curves at various radiation levels and a constant temperature of 25 °C are shown in **(a)** the I-V curve and **(b)** the P-V curve.

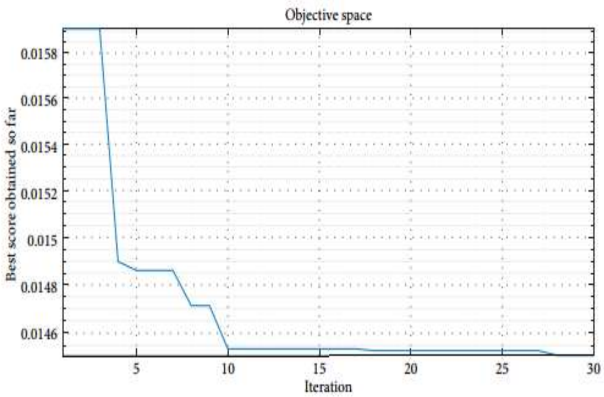


Figure 5. Convergence curve comparison at 20% voltage decreases.

Since no reactive power is being injected, the reactive current, iq = 0, as depicted in **Figure 6**, is zero under typical conditions. As a result, when the failure occurred at 3.5 s, the voltage decreased to 189.82 V, which was more than 20 % of the nominal value. When the load was attached at 4.5 seconds, the voltage continued to decline. The voltage has been risen to 239.6 V thanks to PI and EWOA-FLC based controllers.

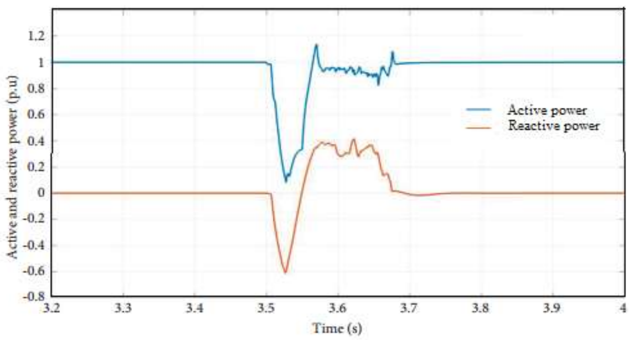


Figure 6. Power supply for the suggested EWOA-FLC controller, both active and reactive.

ANFIS may be generated in 100 epochs using the hybrid control technique and a 0.01 error limit. Soaring **Figure 7** illustrates the learning error.

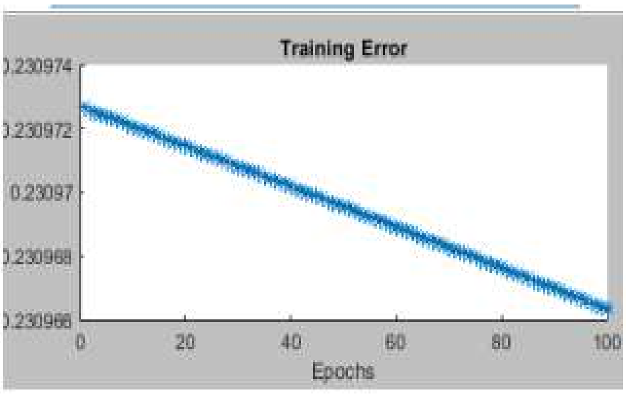


Figure 7. Training error versus epochs for the ANFIS.

As shown in **Figure 8**, the simulation results and the processed size of the PV array agree. Additionally, the PV array modules respond to variations in temperature and irradiance by operating at their maximum power point by monitoring the PV module's highest voltage and current. As a result, the maximum power possible is attained. **Figure 8** shows a comparison of the suggested and current solar PV energy management algorithms. When compared to traditional optimization methods, GTO-based MAS offer increased stability and efficiency. **Table 2** shows that the comparative Analysis of Algorithms for Solar PV Energy Management Based on Energy Efficiency.

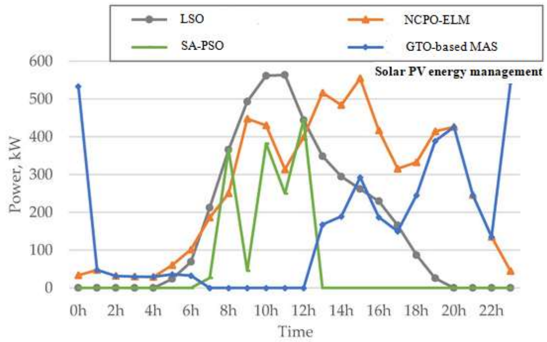


Figure 8. Comparative analysis of proposed vs existing algorithms for solar PV energy management.

Table 2. Comparative analysis of algorithms for solar PV energy management based on energy efficiency comparative analysis of algorithms for solar PV energy management based on energy efficiency.

S. No	Algorithm	Energy efficiency (%)
1.	LSO [11]	25 %
2.	SA-PSO [12]	10 %
3.	NCPO-ELM [3]	30 %
4.	GTO-based MAS (Proposed)	35 % (Best)

5. Conclusion

The proposed solution offers a solar power plant's intelligent energy management framework along with cutting-edge optimization methods and hybrid energy sources. Using an ANFIS controller, the architecture integrates a PV module, utility grid supply, and battery storage. By managing solar irradiance uncertainty and dynamic demand situations, the ANFIS controller effectively controls power flow between generating, storage, and load components. To guarantee steady functioning and longer battery life, a charger subsystem controls battery charging and discharging. Additionally, a MAS based on GTO is used to optimize energy distribution among various loads, including EVs, drones, and portable gadgets, enhancing overall system dependability and efficiency. Proposed GTO-based MAS achieves 35% energy Highest efficiency & stability. Future work can focus on integrating AI-based predictive control and real-time adaptive optimization to further enhance solar PV energy efficiency and system reliability.

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