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Modelling and Analysis of Renewable Energy Integration and Electric Vehicle Impact on Microgrid Performance: The PSO-Based MPPT and ANFIS-Controlled Battery Approach

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Abstract: The rapid rise in pollution levels and green house gas emissions has accelerated an adoption of Electrical Vehicles (EVs), which are expected to play the pivotal role in a future energy landscape. As EVs integrate with electrical grids, their impact on voltage profiles and grid load distribution becomes increasingly significant. This study explores an integration of renewable energy sources, EVs into the microgrid and with the emphasis on energy production and consumption optimization. In this analysis, the diesel generator is a microgrid, Photovoltaic (PV) array coupled with the wind farm and the Vehicle-to-Grid system near a load. A paper introduces the model for a PV array that employs Maximum Power Point Tracking (MPPT) through Particle Swarm Optimization (PSO) to maximize an efficiency of a solar energy conversion. Furthermore, it investigates battery control using Adaptive Neuro-Fuzzy Inference System (ANFIS) to manage a storage and distribution of energy from both renewable sources and EVs. A microgrid is designed to cater to an energy demands of various establishments, including hospitals, universities, and EV charging stations. The comprehensive analysis of a micro grid's performance, with the particular focus on effects of EV integration, is presented using MATLAB/Simulink, revealing an influence of EVs on an overall network stability and energy management.
Keywords: ANFOIS, V2G, EV Vehicles, MATLAB , PSO.

1. Introduction

Transport industry contributes approximately 25 percent of the energy-related emissions, making up a large share of global greenhouse gas emissions. In order to address this issue, electrical vehicles (EVs) have emerged as the viable solution. They are classified as clean and environmentally friendly due to their lack of tailpipe emissions. Several nations are actively promoting an adoption of EVs through incentives and regulations, aiming to foster their widespread integration into a market. However, a growing adoption of EVs is expected to have the an electrical grid. If EV charging remains unregulated, it could lead to increased peak electricity demand, causing grid instability, power losses, and equipment overloads. On an other hand, controlled charging and an use of EVs as distributed energy resources, especially using Vehicle-to-Grid (V2G) technology, could have significant benefits. V2G allows EVs to not only draw power from a grid (Grid-to-Vehicle, G2V) but also discharge energy back into a grid, supporting grid stability, frequency regulation and peak load shaving. The introduction of renewable energy sources (solar and wind energy) into a microgrid, coupled with an adoption of EVs, further enhances a potential

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benefits. The microgrid consisting of the diesel generator, the PV array, the wind farm, and V2G technology can provide the sustainable and reliable power supply to various establishments, such as hospitals, universities, and EV charging stations. an application of Maximum Power Point Tracking through Particle Swarm
Optimization for a PV array and an use of Adaptive Neuro-Fuzzy Inference System for battery control are critical for optimizing energy efficiency and ensuring effective energy storage and distribution.

EVs are categorized into three types: Battery electric vehicle, Hybrid electric vehicle and fuel cell electric vehicles (FCEVs), each contributing to reducing reliance on fossil fuels. Despite concerns about battery life, recent advancements have addressed many of challenges, making EVs the promising alternative to conventional Internal Combustion Engine (ICE) vehicles. A primary challenges associated with V2G technology include managing erratic travel patterns and an optimization of charging schedules to minimize battery wear while maximizing an efficiency of an eV fleet. Additionally, V2G provides an opportunity to enhance a resilience and stability of an electrical grid by balancing loads and integrating renewable energy sources, ultimately helping to flatten an overall load profile and reduce environmental pollution.

This paper uses MATLab/Simulink to model and analyze microgrids, including the integration of renewable energy sources and electric vehicles. We concentrate on how grid performance and operating costs are affected by EV charging patterns, battery efficiency, and V2G technology.

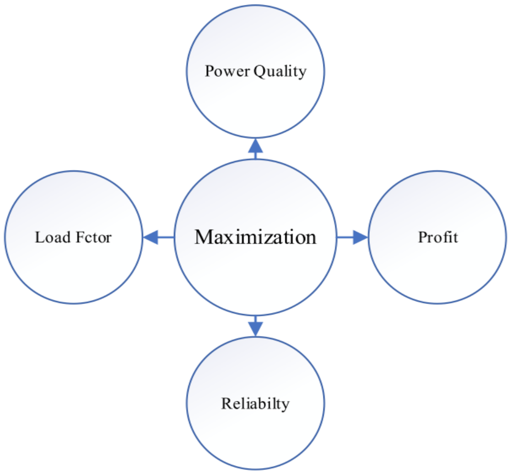

Figure. 1 Maximization objective functions of electrical vehicle integration into a distribution system

Our goal in conducting this analysis is to investigate how EVs can function as decentralized power generation sources that minimize their environmental impact while supporting load balancing and grid stability of both transportation and electricity supply systems.

Standard Charging (Model)

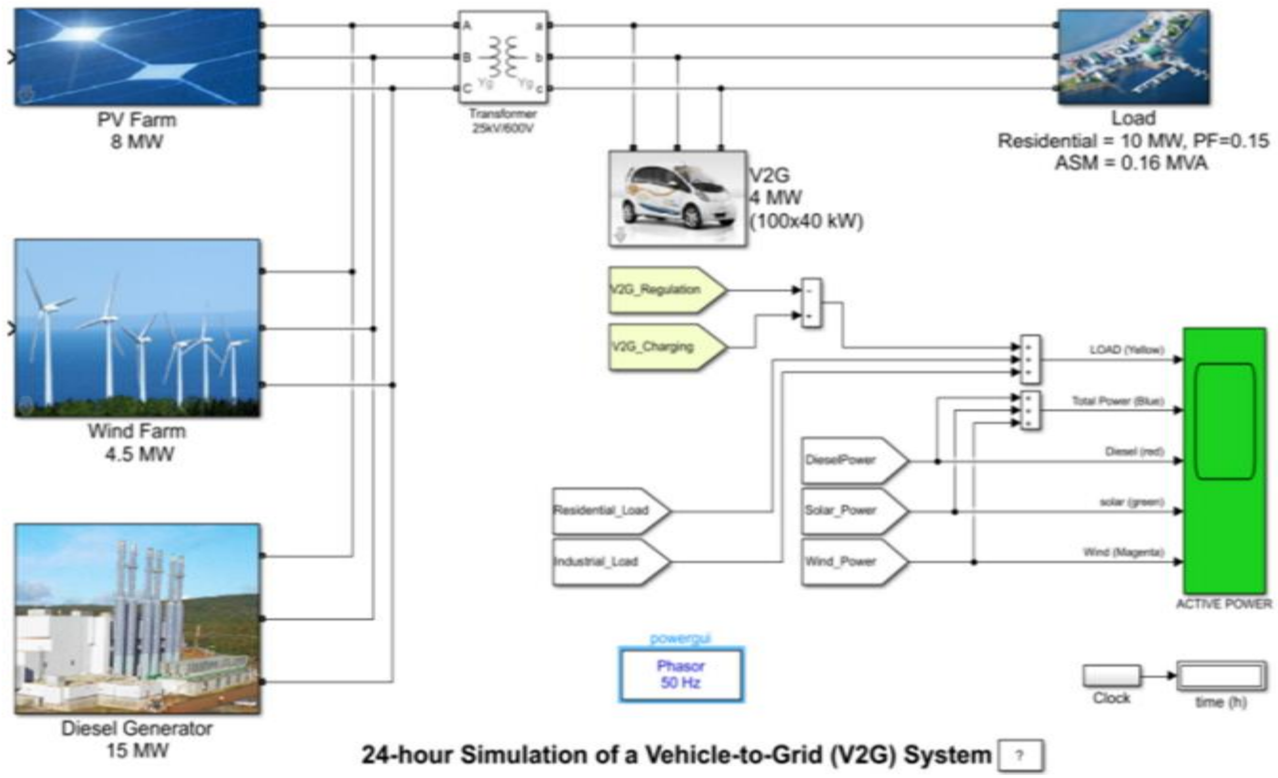

Figure. 2 Microgrid and electrical vehicles

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Microgrid systems rely on a precise management of fundamental quantities like current and voltage and are represented by sinusoidal waveforms at 50 Hz frequency.

2. Photovoltaic System with Particle Swarm Optimization for Maximum Power Point Tracking

Photovoltaic systems are the key component in renewable energy generation. They convert sunlight into electrical energy through solar cells. However, the power output of a PV systems is not constant and varies depending on several factors such as sunlight intensity, temperature and an angle of incidence. The efficiency of a PV system can be maximized by operating at a **maximum power point,** which is a point at which a system produces a highest power output. To track this point dynamically, the **maximum power point tracking** technique is employed. Although many MPPT methods exist, one of the successful one is an application of particle swarm

optimization, which is the heuristic optimization algorithm based on a social behavior of the birds flocking or fish schooling. PSO has been proven to be an efficient method for MPPT in PV systems due to its simplicity, fast convergence, and ability to deal with non-linearities and local maxima.

Maximum Power Point Tracking

MPPT denotes a technique employed in the ongoing pursuit of a maximum power point on the power and voltage graph of the PV module. This method is crucial because it ensures the PV system functions at peak performance, particularly when environmental conditions are variable. The power and voltage characteristics of the PV module usually exhibit a single peak referred to as the MPP. The voltage at this point is referred to as Maximum Power Voltage (Vmp), while the current is termed Maximum Power Current (Imp).

The PV output power depends on various factors:

- **Solar irradiance**: More sunlight results in higher power output.
- **Temperature**: Higher temperatures decrease an efficiency of a PV cells.
- **Shading and dirt**: Partial shading can create multiple peaks on a power curve, making MPPT challenging.

To efficiently track a **MPP**, a system must adjust its operating voltage to match optimal conditions for power generation.

2. Particle Swarm Optimization

Particle swarm optimization is a computation style that is analogous to animal social dynamics of a flock of birds or a school of fish. PSO has been employed in MPPT to vary the operating point of a PV system to maximize power output.

How PSO Works:

Initialization: The group of particles symbolizing a possible solution is set up with random locations and speeds within a search area, like the voltage range for a PV system.

Assessment: for each particle, a fitness function is assessed, which, in the context of MPPT, is the power generated by the PV module at that specific operating voltage.

Velocity and Position Adjustment: Each particle adjusts its velocity and position based on its past experiences and the experiences of its neighbours the best solutions discovered until now using an update rule defined by:

$$v_i(t+1) = wv_i(t) + c_1r_1(p_{best} - x_i) + c_2r_2(g_{best} - x_i)$$

Where:

$v_i(t+1)$ is a velocity of particle iii at time t+1.

w is an inertia weight that controls an exploration and exploitation of a search space.

c_1 and c_2 are a cognitive and social coefficients, respectively, which influence a particle's tendency to explore its own experience or that of a swarm.

r_1 and r_2 are random numbers between 0 and 1.

pbest is a personal best position of particle iii.

gbest is a global best position found by a swarm.

x_i is a current position (voltage) of particle iii.

Convergence: Over time, a swarm converges toward a **maximum power point** by iteratively adjusting a particle positions and velocities.

Wind Energy: Harnessing a Power of Wind for Renewable Energy Generation

One of the most well-known forms of renewable energy is wind. It is an eco-friendly, sustainable, and renewable energy source that can significantly reduce carbon emissions and dependency on fossil fuels. Wind energy is harnessed through wind turbines that transform the kinetic energy of the wind into mechanical energy, subsequently converting it into electricity.

A rising demand for renewable energy, together with increasing worries about climate change, has resulted in a growth in the utilization of wind energy as a key component of the global energy mix.

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Wind Energy Conversion Process

To understand an energy production and efficiency of the wind turbine system, several key mathematical formulas and calculations are used. These include a calculation of **power output** from wind energy, **capacity factor**, and **efficiency** of a turbine. Below are a most commonly used mathematical models for wind energy.

Wind Power Calculation

The power obtained by wind turbine is determined with the help of the formula below:

$$P = \frac{1}{2}\rho A v^3$$

Where,

P = output power (W)

ϱ = Air density (kg/m³) ≈ 1.225 kg/m³ at sea level

A = Area swept by the turbine (m²) A=πr², with r representing the radius of the wind turbine blades.

v = Wind speed (m/s)

This equation is based on the kinetic energy of air through turbine blades. A cube of wind speed is linked with a power.

Power Coefficient

In the wind, a turbine is not able to harness all the energy. The Power Coefficient (Cp) of the wind turbine is used to determine its efficiency taking into account the constraints of the turbine design and the Betz Limit (that the optimum energy that can be harnessed in the wind turbine is 59.3%).

$$P_{turbine} = \frac{1}{2}\rho A v^3 \cdot C_p$$

Where,

$P_{turbine}$ = Power extracted by the turbine (W)

C_p = Power coefficient (usually ranges from 0.3 to 0.5 for conventional wind turbines)

The value of Cp is typically less than 1, and a Betz Limit states that Cp can never exceed 0.593

Energy Output over Time

To calculate a total energy produced by the wind turbine for the given period, we use a following formula:

$$E = P_{turbine} \times t$$

Where:

E = Energy output (Wh or kWh)

$P_{turbine}$ = Power extracted by a turbine (W)

t = Time (hours)

This gives an energy produced by a turbine in kilowatt-hours or watt-hours for the specified time period.

Capacity Factor

The primary metric that characterizes a wind turbine's actual energy production in relation to its theoretical maximum output is the capacity factor (CF). It is the measure of how effectively the turbine operates over time.

$$CF = \frac{E_{actual}}{E_{max}} \times 100$$

Where:

- E_{actual}= Actual energy production during the duration (kWh).
- E_{max}= Maximum possible energy output if a turbine operated at full capacity all a time (kWh).

Capacity factors change according to the wind conditions, however, the standard range of onshore wind turbines is between 20 percent and 40 percent, while offshore wind turbines may have the higher capacity factor (up to 50%).

Tip Speed Ratio

The ratio between the velocity of a blade tip and that of the wind is referred to as tip speed ratio. It is a significant consider in the design of wind turbines, as this affects power efficiency.

$$TSR = \frac{r \cdot \omega}{v}$$

Where:

- r = Radius of a turbine blades (m).
- ω = Angular speed of a rotor (rad/s).
- v = Wind velocity (m/s).

A higher TSR denotes more efficient operation at high wind speeds, and a typical TSR for optimal wind turbine efficiency is between 6 and 10.

Wind Turbine Efficiency

The efficiency of the wind turbine is generally is calculated using the ratio of energy extracted from a wind to energy available in a wind.

$$\eta = \frac{P_{turbine}}{P_{wind}} \times 100$$

Where:

η = Efficiency (%)

$P_{turbine}$ = Power extracted by a turbine (W)

P_{wind} = Power available in a wind (W)

Most commonly, the maximum efficiency is limited by the Betz Limit that no wind turbine is allowed to collect over 59.3% of the energy in the wind.

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Sizing Wind Turbines and Energy Generation

To determine the wind turbine's appropriate size for the specific site, it is frequently essential to compute the annual energy output based on the turbine's power curve and average wind speed. The turbine power curve illustrates how much power a turbine produces at various wind speeds. An estimate can be made by:

$$P(v) = P_{rated} \times \left(\frac{v}{v_{rated}}\right)^k \quad \text{for} \quad v < v_{rated}$$

Where:

$P(v)$ = Power output at wind speed v

P_{rated} = Rated power of a turbine at v_{rated}

v_{rated} = Rated wind speed (typically 12–15 m/s)

k = Empirical coefficient for a turbine (typically between 2 and 3)

The annual energy production (AEP) is then calculated as:

$$AEP = \sum_{i=1}^{n} P(v_i) \times \Delta t$$

Where:

v_i is a wind speed at time iii,

Δt is a time interval,

n is a number of time intervals.

This calculation bears an overall amount of electricity produced by a wind turbine over the year, taking into account the varying wind speeds.

Wind Energy Cost Calculations

An important economic metric for assessing the cost of generating electricity with wind turbines is the levelized cost of energy. The price by which energy should be sold so that the project can attain a break-even point and to cover the initial investment, operation and maintenance costs.

The equation for LCOE is:

$$LCOE = \frac{\sum_{t=1}^{N} (C_t + O_t)}{\sum_{t=1}^{N} E_t}$$

Where:

- C_t = Capital costs in year t.
- O_t = Operating and maintenance costs in year t.
- E_t = Energy produced in year t.
- N = Project lifetime (commonly 20–25 years).

LCOE helps in comparing wind energy with other energies. Sources on the basis of cost-efficiency. It is these mathematical formulas that give the explanation behind Understanding how wind turbine generates energy, their efficiency, and the amount of energy they can generate over a period of time. These calculations are highly significant in knowing and using wind optimization. Wind energy technologies, energy systems, determining the feasibility of the project, and comparing a performance of various turbine designs.

Diesel Energy

In a context of the diesel generator or power plant, a Following key calculations are used in obtaining an energy output, fuel consumption, and efficiency of a system. Diesel generators have an extensive usage in backup power applications, off-grid power generation, and distributed energy systems owing to their reliability. and relatively simple operation. Below are major mathematical formulas used in calculating diesel energy production and efficiency?

Diesel Generator Output

The output of the diesel generator depends on on an engine's rated power. A power produced given by the diesel engine is usually expressed in kilowatts (kW) and it can be computed using the formula:

$$P = \frac{T \times N}{9549}$$

Where:

P = Power output of a diesel engine (kW).

T = Torque produced by an engine (Nm).

N = Rotational speed of an engine (RPM).

Alternatively, power output is often rated directly by a manufacturer and expressed as kW or kVA (kilovolt-amperes).

Fuel Consumption Calculation

The fuel consumption of the diesel generator depends on its fuel consumption rate, which is usually provided by a manufacturer. It is commonly given in terms of liters per kilowatt-hour (L/kWh). A fuel consumption can be estimated using the following formula:

$$\text{Fuel Consumption} = \text{Power Output} \times \text{Fuel Consumption Rate}$$

Where:

Fuel Consumption = Fuel consumed (liters per hour, L/h)

Power Output = Power produced by a diesel engine (kW)

Fuel Consumption Rate = a fuel consumption rate in liters per kWh (L/kWh)

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For example, if a fuel consumption rate of a generator is 0.2 L/kWh, and a generator is producing 10 kW, the fuel consumption would be:

$$\text{Fuel Consumption} = 10\,\text{kW} \times 0.2\,\text{L/kWh} = 2\,\text{L/h}$$

Thus, a generator would consume 2 liters of diesel fuel every hour of operation.

Diesel Generator Efficiency

The efficiency of the diesel generator is a ratio of a Mechanical power produced by an engine to an Energy content of a fuel consumed. It can be calculated as:

$$\eta = \frac{P_{out}}{P_{fuel}} \times 100$$

Where:

η = Efficiency of a diesel generator (%)

P_{out} = Power output of a diesel engine (kW)

P_{fuel} = Power content of a fuel (kW)

To calculate Pfuel, you need to know an energy content of a diesel fuel (in kWh per liter or kWh per gallon). Diesel typically has an energy content of about 35.8 MJ/L (megajoules per liter) or approximately 9.94 kWh/L.

$$P_{fuel} = \text{Fuel Consumption (L/h)} \times \text{Energy Content (kWh/L)}$$

For instance, if a diesel consumption is 2 L/h and an energy content is 9.94 kWh/L, a power content from a fuel would be:

$$P_{fuel} = 2\,\text{L/h} \times 9.94\,\text{kWh/L} = 19.88\,\text{kWh}$$

The efficiency can then be calculated by dividing a power output by a fuel power:

$$\eta = \frac{10\,\text{kW}}{19.88\,\text{kW}} \times 100 = 50.37\%$$

So a diesel generator's efficiency is approximately 50.37%.

Diesel Fuel Cost Calculation

To estimate a cost of a fuel required for the diesel generator, we use a following formula:

$$\text{Fuel Cost} = \text{Fuel Consumption} \times \text{Fuel Price}$$

Where:

Fuel Cost = Cost of a fuel consumed (in local currency, e.g., USD)

Fuel Consumption = Amount of fuel consumed (liters per hour, L/h)

Fuel Price = Price of a fuel per liter (currency per liter)

For example, if a generator consumes 2 liters of diesel per hour and a price of diesel is $1.2 per liter, a cost of fuel per hour would be:

Total Energy Produced by the Diesel Generator over Time

To calculate a total energy produced over the given period, we multiply a power output by an operating time:

$$E = P \times t$$

Where:

E = Total energy generated (kWh)

P = Output power of a diesel generator (kW)

t = Duration of the operation (hours)

For example, when the diesel generator operates at 10 W for 5 hours results in a total energy output of :

$$E = 10\,\text{kW} \times 5\,\text{hours} = 50\,\text{kWh}$$

ANFIS Based Battery Controller

The Adaptive Nero-Fuzzy Inference System is an advanced control method that integrates Neural Networks and Fuzzy Logic to provide the powerful solution for battery control systems. ANFIS is particularly effective in situations in which traditional mathematical models are difficult to apply, and it excels in learning from data and adapting to various system dynamics. In battery control, ANFIS can optimize charging and discharging processes, extending battery life. Improvement of performance while ensuring efficiency of a system.

Overview of Battery Management System

A battery management system is used to guarantee that the battery is used in a safe and efficient way. The primary roles of the BMS consist of:

- Observing a battery's charge level, health status, and temperature.
- Control the charge/discharge process in order to
- prevent overcharge or deep discharge, which could worsen the performance of a battery or even damage it.
- Balancing a cells to ensure uniform voltage levels
- across all cells.
- Improving the efficiency and lifespan of a battery.

To achieve this, the BMS requires intelligent algorithms that adjust a control parameters based on real-time feedback from a system..

Battery Control Using ANFIS

ANFIS is the hybrid model in which a neural network and

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fuzzy logic systems. It is well-suited for battery management systems because it can handle uncertainties, nonlinearities, and vagueness in system behaviour. Here's how ANFIS can be used for battery control:

Control Process with ANFIS

ANFIS Training:

- Control Process with ANFIS the ANFIS model can be trained using either historical data or simulation data, where a system learns to associate an input with a desired output. A training process adjusts a fuzzy membership functions, enhancing a system's accuracy in predicting and controlling a charging/discharging actions.
- The training process involves minimizing the cost function, which measures an error between a predicted and actual battery conditions.

Output: an output of an ANFIS system is the control action that is sent to a Battery Management System to regulate a battery's charging or discharging. A control action can be:

- Adjusting a charging current or voltage.
- Adjusting a load applied to a battery.
- Deciding when to switch between charging and discharging modes.

The fuzzy system can output values like:

- Charging Current: "High", "Medium", "Low"
- Discharge Current: "High", "Moderate", "Low"
- State of Charge (SOC): Maintaining an optimal SOC range.

ANFIS Structure for Battery Control

The basic structure of an ANFIS system involves multiple layers:

Layer 1 (Fuzzification Layer):

- Each node in this layer represents the fuzzy membership function for each input (SOC, voltage, temperature, and load).
- The outputs of this layer are membership degrees that represent how much an input belongs to the particular fuzzy set.

Layer 2 (Rule Layer):

- Each node represents the fuzzy rule (e.g., "IF SOC is Low AND Load is heavy THEN Charging Rate is high").
- The output is a firing strength of a rule, which is a product of a membership values.

Layer 3 (Normalization Layer):

- This layer normalizes firing strengths of rules to ensure that outputs are within an appropriate range.

Layer 4 (Defuzzification Layer):

In this layer, the outputs of fuzzy rules are aggregated according to their firing strengths. A result is the weighted mean that signifies a system's control operation.

Layer 5 (Output Layer):

- This layer produces a final output of a system, which is a control action (e.g., charging current, discharging rate).

Application Example: Battery Charging Control Using ANFIS

In the solar PV-based energy storage system, an ANFIS-based battery control system can be used to regulate a charging of batteries from a PV array. an inputs to an ANFIS might be:

- The solar power generation (related to sunlight intensity),
- The battery SOC,
- The battery voltage,
- The ambient temperature.

The output of an ANFIS system could be the control action that decides an optimal charging rate for a battery, ensuring that a battery charges efficiently without overcharging, and maintaining a SOC in a desired range.

ANFIS is the powerful tool for controlling battery systems, especially in cases where battery behaviour is complex and nonlinear. By combining fuzzy logic's ability to handle uncertainty with learning capabilities of neural networks, ANFIS can optimize a charging and discharging process, improve battery life, and enhance an overall performance of energy storage systems.

RESULTS

Power Generation Profile

The power output of the generator varies throughout a day based on a load demand, environmental conditions, and an operating cycle of a generator. To analyze a electricity produced by the diesel generator or any generator over the course of a day, we typically need to consider several factors including operational hours, load profile, fuel consumption, efficiency, and environmental factors (i.e. temperature, humidity, etc.).

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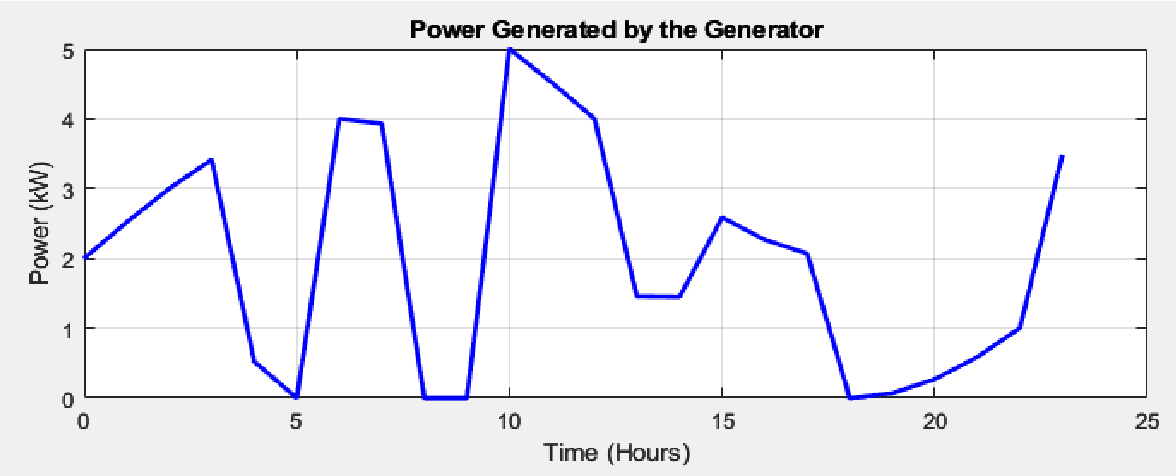

Figure. 3 A generators daily output of electricity

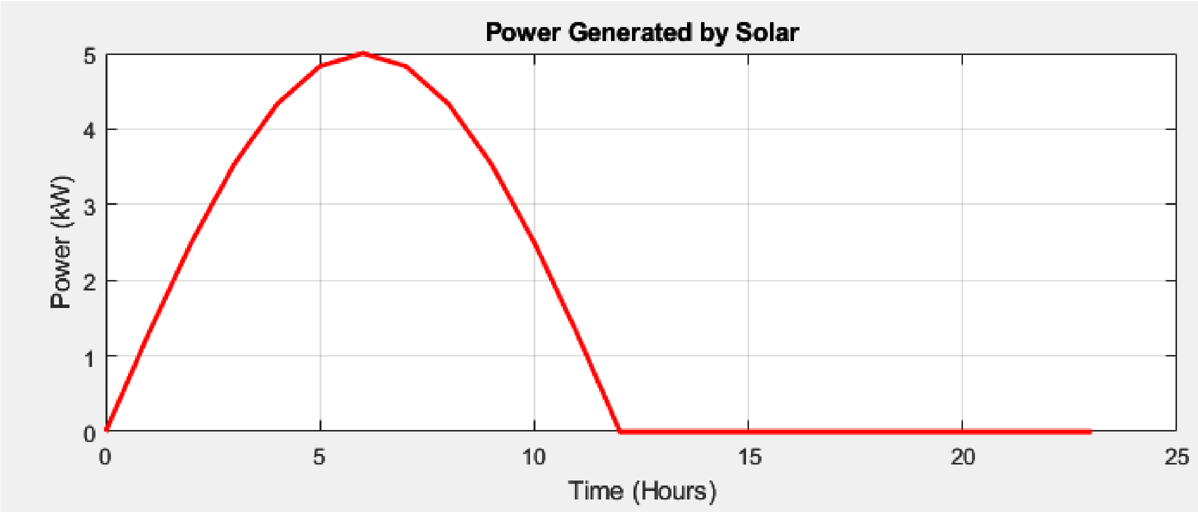

Figure. 4 Solar energy produced over the course of the day

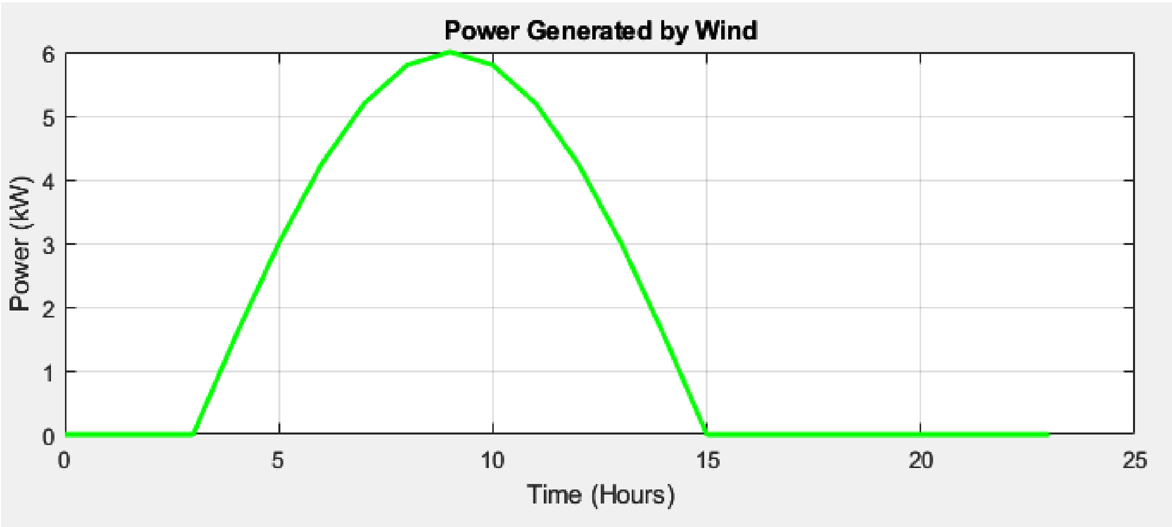

Figure. 5 Wind-generated energy throughout the day

The swift expansion of Electric Vehicles (EVs) has led to the significant increase in power demand, adding extra strain on a microgrid. This rise in demand also amplifies variability within a grid. To balance electricity consumption with generation, a diesel generator in a microgrid plays the key role. Discrepancies in grid frequency can be detected by comparing a rotor speed of a synchronous machine. Figure 4 shows a total energy output from a diesel generator throughout a day. However, diesel generators come with major drawbacks, including high costs and harmful

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environmental effects. Despite these disadvantages, diesel generators remain necessary when renewable energy sources are unable to meet a required energy demand. A microgrid relies on two renewable energy sources:

Figure 5 illustrates a daily energy production from a solar panels, where an use of PSO for MPPT ensures that a maximum possible energy is harvested from a solar radiation available, even under fluctuating environmental conditions. By optimizing a performance of a PV system, PSO helps enhance an overall efficiency and reliability of a microgrid.

Wind Farm: a wind farm generates electricity proportional to a wind speed. Turbines reach their maximum power output once a wind speed exceeds the specified threshold. If a wind speed exceeds this limit, a wind power generation is deactivated until a wind returns to optimal conditions. Figure 6 shows a daily energy output of a wind farm within a microgrid.

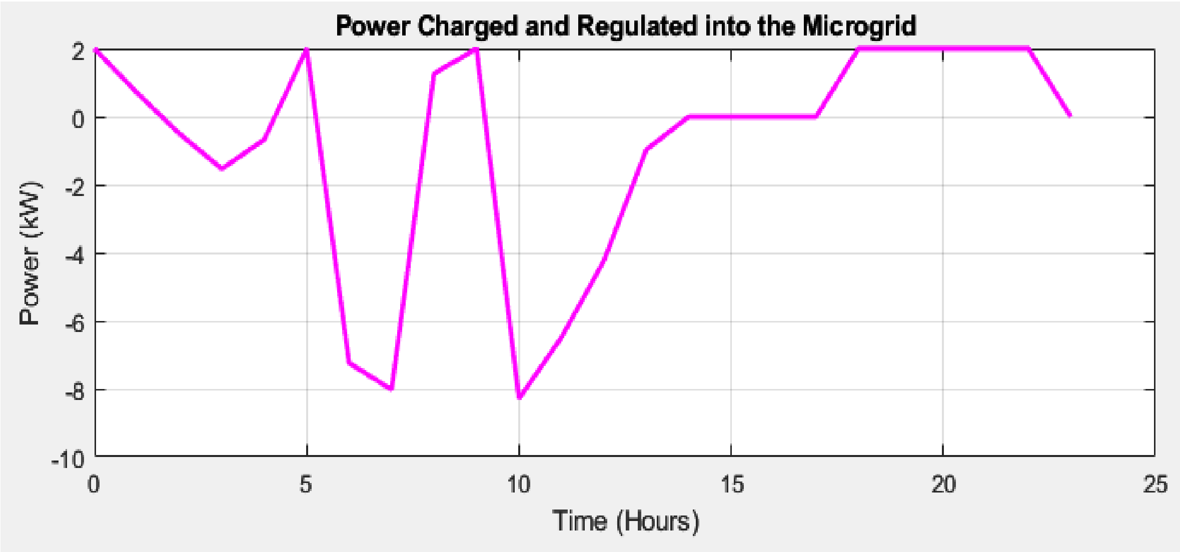

Figure. 6 Charged and regulated into a microgrid throughout a day

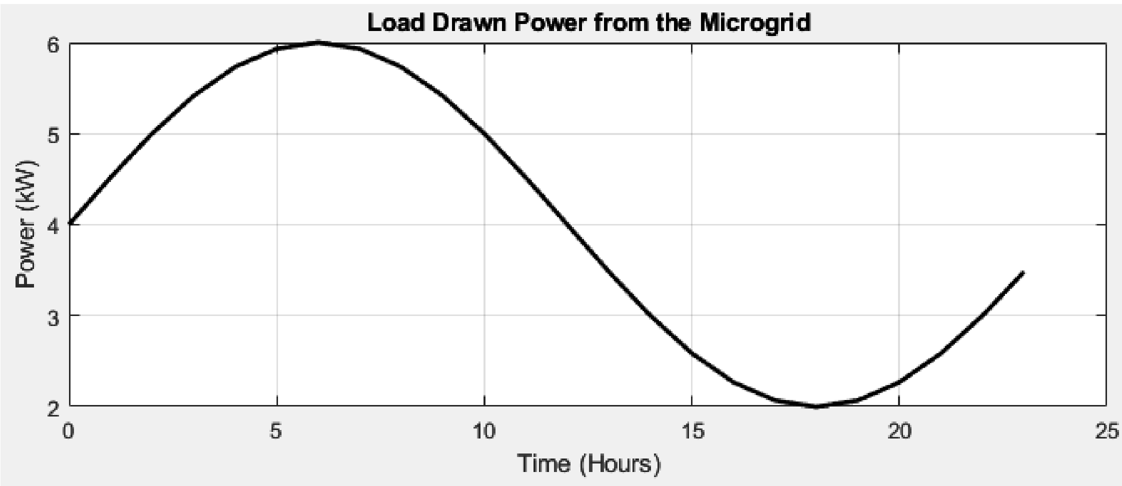

Figure. 7 Load drawn power from a microgrid during a day

The integration of wind energy facilities in microgrids is consistently rising because of their sustainable characteristics, straightforward design, and great efficiency. Unlike traditional power plants, wind farms offer unique characteristics that make them an appealing energy source for microgrids. Similarly, Electric Vehicles (EVs) provide the significant advantage due to their ability to support Vehicle-to-Grid (V2G) applications, the feature unique to electric cars. V2G enables EVs to directly supply electricity back to a distribution microgrid, contributing to grid stability. Figure 7 illustrates a power transmitted and regulated by an eV to a microgrid throughout a day.

V2G refers to a process by which EVs transfer stored electrical energy from their batteries back into a microgrid. A battery in these vehicles act as energy storage systems, and Car-to-Grid (C2G) technology enables a controlled charging and discharging of an eV battery based on various factors, such as energy demand or supply signals.

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However, as a number of EVs being charged increases, an electrical demand per transformer also rises, particularly during peak consumption periods in a microgrid. This can pose challenges in maintaining an energy balance within a system [16].

When multiple EVs are charged simultaneously within a same phase, phase imbalances can occur in a microgrid. Spontaneous and uncoordinated charging of numerous EVs introduces several issues, including voltage drops at chargers' connectors. Additionally, a high active power draw during simultaneous EV charging can result in power losses, further destabilizing a microgrid.

To address these challenges, an Adaptive Neuro-Fuzzy Inference System (ANFIS) controller can be implemented. an ANFIS controller optimizes a charging and discharging cycles of EV batteries based on real-time grid conditions and energy demands [17].

By dynamically adjusting a charging rates and coordinating a load distribution, an ANFIS controller ensures that a microgrid remains balanced, preventing phase imbalances, voltage drops, and power losses. This intelligent control mechanism helps to maintain an overall stability and efficiency of a microgrid, even during periods of high EV charging.

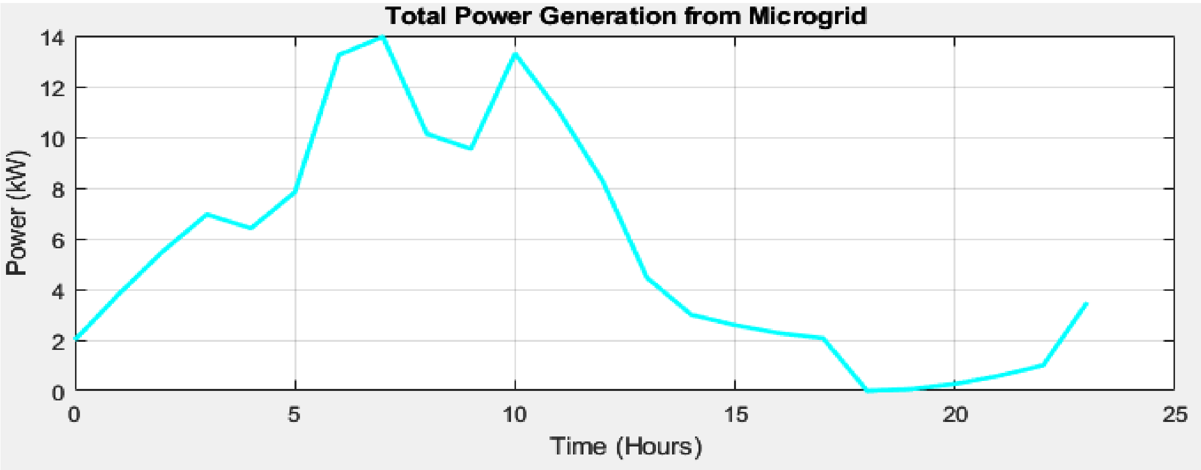

Figure. 8 Total power generation from micro grid during a day

V2G technology, in conjunction with an Adaptive Neuro-Fuzzy Inference System (ANFIS), serves two main purposes: managing battery charge and utilizing an available power to stabilize a grid during transient events. ANFIS enhances an efficiency of V2G systems by providing an adaptive and intelligent control mechanism, allowing for dynamic optimization of energy storage and distribution. This ensures that current decentralized energy storage systems are readily available and efficiently managed. Various battery types are available in a market, and ANFIS can be used to optimize their performance based on real-time grid conditions.

The residential load is represented by an active power drawn at the specified power factor, as shown in Figure 8. With ANFIS, a charging and discharging cycles of EV batteries are precisely controlled to align with a grid's demand. A total power generated by a microgrid is represented by an active power produced, and this power must be equal to or exceed a load. an ANFIS controller ensures that a balance between energy demand and generation is maintained by optimizing battery operations in real-time, as illustrated in Figure 9.

Conclusion

This study demonstrates a significant role of Electrical Vehicles (EVs) in shaping a future energy landscape, especially when integrated into the microgrid environment. By combining renewable energy sources such as Photovoltaic (PV) arrays and wind farms with the Vehicle-to-Grid (V2G) system, alongside efficient energy storage managed by Adaptive Neuro-Fuzzy Inference System (ANFIS), a proposed microgrid can enhance energy production, consumption, and overall network stability. an use of Particle Swarm Optimization (PSO) for Maximum Power Point Tracking (MPPT) optimizes solar energy conversion, ensuring higher efficiency. an integration of EVs into a microgrid was shown to have the profound impact on voltage profiles and load distribution, underscoring a need for effective management strategies. This research provides valuable insights into how microgrid systems, particularly in establishments like hospitals, universities, and EV charging stations, can better adapt to an increasing demand for clean and reliable energy. Simulation results from Matlab/Simulink further validate a feasibility and effectiveness of these systems in maintaining stability, optimizing performance, and supporting the sustainable, low-emission future.

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