Hybrid SFLA-ANN Method for Effective Power Management of Hybrid Power Sources in a Variety of Weather Scenarios

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Abstract: An intelligent Hybrid Energy Management Control model (HEMC) is utilized in grid integrates hybrid renewable energy system. This system incorporates a primary source in the form of a solar photovoltaic (PV), followed by wind power, storage element consisting of a Super Capacitor and supporting element of grid. To ensure optimal operation, a perceptive mode-based controller is employed in HEMC model, which utilizes a Shuffled Frog Leaping Algorithm with trained Artificial Neural Network (SFLA-ANN). The objective function is to minimize the transient power oscillations and settling time during static and dynamic load change condition with different environmental climatic conditions. To evaluate its performance, it is compared with existing algorithms such as Sliding Mode Controller (SMC), Shuffled Frog Leaping Algorithm (SFLA) and Sliding Mode Controller – Artificial Neural Network (SMC-ANN), which have been implemented using the Simulink/MATLAB Platform. The analytical output response of HEMC presented and reflects significant performance improvement of the proposed controller is tested under both static and dynamic load conditions.

Keywords: Sliding Mode Controller, Super Capacitor, Photovoltaic Cell, ANN, Shuffled Frog Leaping Algorithm.

1. Introduction

The essence of the global challenge is represented by the climate changes and the renewable energy plays an important role in mitigating it. The burning of fossil fuels for energy generation is a significant contributor to the accumulation of greenhouse gases in the atmosphere, leading to global warming and climate change. Fossil fuel reserves are finite and are being depleted rapidly due to extensive usage. This reality necessitates a shift towards sustainable and renewable energy sources. Renewable energy sources such as wind, solar, tidal, biomass, and hydro micro turbines offer a sustainable alternative to fossil fuels. These sources are abundant, clean, and replenishable. Significant efforts are being directed towards research and development in renewable energy technologies to make them more efficient, affordable, and accessible.

In addition to primary renewable energy sources, secondary storage technologies such as hydrogen fuel cells, super capacitors (SC), and batteries play a crucial role in storing and efficiently utilizing renewable energy, thereby enhancing its reliability and stability in the electricity grid. Renewable energy systems inherently produce fewer or zero emissions compared to fossil fuel-based energy generation, contributing to the reduction of greenhouse gas emissions and combating climate change. In conclusion, the transition to renewable energy is imperative to mitigate the impacts of climate change, ensure energy security, and foster sustainable development for future generations.

Akram et al. (2017) presented a methodology for optimizing sources of renewable energy and hybrid power reserve arrangements in a grid-connected micro grid, with the aim of minimizing cost, improving reliability, and reducing greenhouse gas emissions.

The methodology proposed in (Sandhu & Mahesh, 2018) explores the impact of demand side management in hybrid PV and wind/battery energy setup, for optimization purposes. Also, the Pigeon Inspired Algorithm has been employed and an energy filter algorithm was created to reduce the oscillations.

This paper explored an inverter control scheme for wind energy systems under weak grid conditions. It addressed transient issues and slow dynamic response due to unpredictable wind speed and generator inertia which were also approached in (Rahul & Suhag, 2018). The article introduces a hybrid Maximum Power Point Tracking (MPPT) method using an Adaptive Neuro-Fuzzy Inference System-Particle Swarm Optimization (ANFIS-PSO) to efficiently extract PV power with zero oscillation tracking (Priyadarshi et al., 2020). This method eliminates the need for additional sensors for irradiance and temperature measurements, enhancing PV potential extraction.

The research (Benadli et al., 2021) explores the use of sliding mode control in a hybrid system for renewable energy that includes a photovoltaic system and a wind turbine, with a permanent

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magnet synchronous generator connected via a DC/DC converter. The paper (Elnozahy et al., 2021) compares and analyzes three types of controllers in DC-AC inverters in hybrid renewable energy source systems, using sliding mode control and artificial neural network techniques. A sliding mode control technique (SMC) used to improve PV power by minimizing oscillation around the operating point, thus achieving smoother peak power under various conditions, was reported in (Mostafa et al., 2020). In the research proposed in (Khatibi et al., 2022), it was aimed to develop a grid-connected hybrid renewable electricity system with the intention of providing Yazd City from Iran structures the required electricity using genetic algorithms and TRNSYS software. In the studied region, the use of batteries was not adequate.

The article (Priyadarshi et al., 2023) presented a hybrid wind-photovoltaic micro grid system, controlled by a sliding mode controller, achieving maximum power point tracking using a hybrid fuzzy logic controller optimized through particle swarm optimization. The result was that the system achieved peak PV power with simplified implementation and high convergence speed.

The article pointed out that the hybrid power system is a renewable energy generation strategy utilizing photovoltaic panels, battery storage, and solid oxide fuel cells, with an adaptive neural fuzzy inference system trained on Double Integral Sliding Mode Controller (DI-SMC), as presented in (Banu et al., 2022).

The objective of this study (Kalvinathan & Chitra, 2022) is to combine a hybrid control system consisting of a developed artificial neuro fuzzy system (SMC-ANFIS) and a slide mode controller to achieved optimal transient response under dynamic load conditions.

The radial basis function network with deep learning is outlined within the MPPT approach, enhancing accuracy and convergence speed. The boosted slap swarm optimization approach is used for quicker reaction time. The suggested approach is outperforming in terms of global MPPT, the recommended method performs better than fuzzy logic-based neural network and traditional MPPT methods, thus resulting the power and efficiency described in (Raj & Samuel, 2022). The paper (Roumila et al., 2017) worked out fuzzy logic controller for energy management in a hybrid wind, solar, and diesel system with storage battery. This study demonstrates the simplicity and ease of determining operating process based on weather conditions. The research studied about hybrid renewable energy associated with a reliable energy source, which is provided to the consumer, end user or distributed generation through appropriate control design and energy management mechanism. The appropriate storage backup option was used in the metaheuristic algorithm, with a finer-grained solution being obtained, as demonstrated by the results in (Saharia et al., 2018). Lamzouri et al. (2021) used a new and effective output power control method for a hybrid electric generator system, combining sliding mode control and integral action to regulate output power and extend battery life cycle, demonstrating robustness against environmental changes.

In the article (Li et al., 2020), a control system for a combined energy system using MPPT algorithm with fuzzy logic controller was developed and shuffled a frog leaping algorithm was modified for optimal parameters, achieving an efficiency of 99%. Guo et al. (2021) designed a MPPT technique for solar PV systems, combining incremental conductance and a hybrid SFLA-PS-based adaptive neuro-fuzzy inference system, to generate optimal voltages and maximize power points.

The paper (Chandan et al., 2020) analyzed the hybrid electric system performance using MATLAB/Simulink. It developed a model incorporating a battery, fuel cell, and super-capacitor, focusing on energy management and load demand regulation. Thus, the simulation outcomes confirm overall performance in the MATLAB/Simulink environment.

The method proposed by Yasin (2019) for power balance control in a hybrid multisource DC micro grid system aimed to meet load power demand and stabilize DC bus voltage. The experimental results showed that the dynamic and static performance was improved. The paper (Nedim et al., 2023) introduced an intelligent mode-based controller that integrated hybrid non-conventional power with a hybrid energy management control model for optimal operation. It used a shuffled frog leaping algorithm, based on artificial neural networks, and implemented in MATLAB/Simulink. The research (Masry et al., 2023) discussed a maximum power point tracking method for solar PV systems with ANN-

VSP & O-FLC algorithm-based controller. The obtained results showed both low distortions and low oscillations.

Samuel & Rajan (2015) proposed dual algorithms to solve the long-term generation maintenance scheduling problem in power systems, with the help of the designed hybrid particle swarm optimization-based genetic algorithm and hybrid particle swarm optimization-based shuffling frog leaping algorithm. The result demonstrated that, during the planning period, the best maintenance program was achieved.

In the paper (Momen et al., 2023) a framework for optimizing energy consumption in micro grid using the improved shuffled frog leaping algorithm (ISFLA) is proposed, in order to address load uncertainties and renewable energy production probability.

The paper (Ullah et al., 2023) offered a summary of the hybrid micro grid's energy management and control, recommending the use of the most widely used control techniques, including proportional integral derivative, fuzzy logic, artificial neural networks, and sliding mode controllers.

In their work, Chiu & Ngo (2023) presented the hybrid MPPT method, and scrambled frog leaping algorithm combined and incremental conductance, which effectively located the maximum power region. The incremental conductance searching phase precisely discovered MPP. In the research described in (Nie & Nie, 2017), a MPPT-based particle swarm optimization and an improved shuffled frog leaping algorithm were used to address the nonlinear optimization extreme point problems and to overcome the measurement noise effects in complex environments.

Based on this background information, the primary contribution of this study is to suggest a SMC in the presence of severe modeling errors and disturbances. This is because the high switching frequencies and significant management effort required may cause the plant's high-frequency modes to be unintentionally excited. Consequently, this work suggests a higher computational cost for SMC-ANN, which leads to the SFLA high-dimensional difficulties. The traditional sliding mode controller occasionally causes a steady state mistake. To ensure that, the present research first addresses the aforementioned shortcomings of controllers, and then suggests a methodology of SFLA-ANN. Thus, minimal oscillation amplitude, reduced steady state inaccuracy, and shortened switching operation adjustment time can be observed.

The main objectives of the suggested research are to design and test the hybrid power architecture with PV power, wind power, SC and grid backup. The SFLA-ANN algorithm governs this hybrid configuration inverter which is the main instrument for directing and optimizing the combined configuration, including nonlinear outcomes of PV and wind configurations.

This paper is structured as follows. Section 2 presents the system architecture. Next, the power management controllers are outlined in Section 3. Then, the experimental results are considered in Section 4 and, eventually, Section 5 draws the conclusions of the study.

2. System Architecture

2.1 Proposed Methodology for Efficient HEMC

The DC/DC boost conversion system is connected to the wind and photovoltaic sources. The grid's output voltage is connected to the DC bus via an AC/DC converter, and the storage device SC is connected to a bi-directional (BID) DC buck-boost converter. Every DC power conversion system is linked to the DC bus, then the common DC link capacitor and filter are used to feed power to the DC/AC voltage source inverter (VSI), which, in turn, supplies power to the RL load. The control reference signal for VSI, produced by the suggested controller, illustrates the comparison between the DC bus voltage (Vdc) of the common DC link capacitor and the load parameter. SMC, SFLA, SMC-ANN, and SFLA-ANN controllers are among the four energy management strategies used to operate all of the power conversion systems. A grid-integrated hybrid renewable energy system is seen in Figure 1. It comprises photovoltaic (PV) energy, wind energy and super capacitor (SC). The maximum power point tracking boost converters are used to link these sources. This VSI is used to stabilize the voltage during dynamic load changes. This study proposes the use of the SFLA-ANN algorithm to regulate the DC bus voltage, manage the SC charging and discharging, also control the VSI. This proposed algorithm aims to maintain the rated AC voltage profile at VSI's output point, especially during dynamic load variations. The proposed SFLA-ANN algorithm serves two primary functions:

- DC bus voltage management and supercapacitor charge and discharge supervision;
- Controlling VSI and ensuring the rated profile of AC voltage at VSI's output point, during dynamic changes in load conditions.

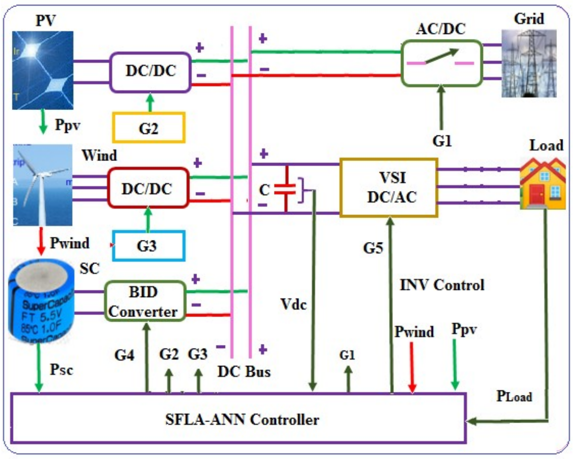

Figure 1. Proposed HEMC

2.2 Solar PV Modeling

The characteristics of a solar photovoltaic module include its single diode model parameters such as I_{SC} (short-circuit current), V_{OC} (open-circuit voltage), and P_{max} (maximum power output), but also the f shunt resistance (R_{Sh}) and series resistance (R_S) can be mentioned as part of the model. This model specification is Soltech ISTH-215-P, I_{SC} - 8.95 A, V_{OC} - 45.22V, Power (P_{max}) – 315 W.

2.3 Wind Energy Modeling

The AC power generated from wind generator is proportional to wind speed. The generated AC voltage from Permanent Magnet Synchronous Generator (PMSG) is fed to DC bus after conversion, through a bridge diode rectifier. The values of the wind model parameters are the following: the wind velocity is 9 m/s, the rated power of the wind turbine is 2.5 kW, the rated speed of the PMSG is 4000 rpm and the operating voltage is 100V AC.

2.4 Super Capacitor (SC) Modeling

The supercapacitor has a large amount of potential energy that would be stored, charged and discharged rapidly. This SC device is used under dynamic load conditions and represents a backup in case of renewable energy source deficiency.

2.5 Power Management Strategy (PMS)

The HEMC has a wide range of sources which are necessary in order to implement the best power management system. In order to achieve this, five distinct modes have been devised for ideal performance under RL load circumstances. As it can be seen in Figure 2, the proposed HEMC controller exerts a variety of configurations in order to provide smooth operations.

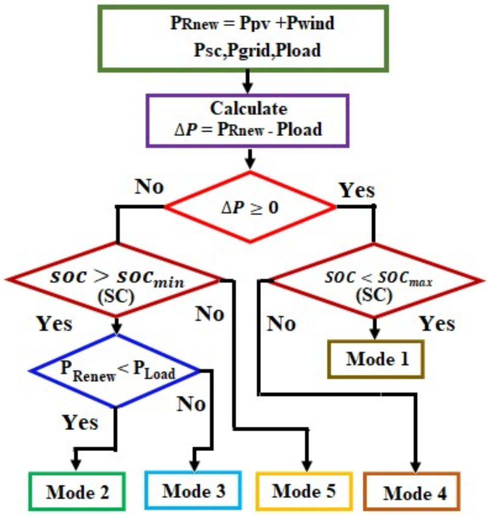

Figure 2. Configuration of HEMC

The variety of configurations is as follows:

Mode 1: This mode utilizes power from solar PV, wind, and the grid to manage the load. Any excess power is used to charge the capacitor;

Mode 2: In order to guarantee sufficient power for the load, the wind velocity and PV insolation are decreased, while grid power remains constant. During this time, the super capacitor is in charging mode;

Mode 3: SC's power is discharged to the load, due to grid operation in isolation, and both PV and wind powers are deviated;

Mode 4: PV insolation is dynamically reduced, while wind velocity is maintained. The super capacitor is fully discharged, and grid power manages the load, with surplus voltage used to charge the SC device;

Mode 5: If the wind source is deficient, the grid and PV system manage the load.

These modes demonstrate a comprehensive approach to managing a hybrid renewable energy system under various conditions, optimizing power utilization, and ensuring continuous supply to the load. The energy management strategy is designed to dynamically adapt to changes in renewable energy generation and to grid conditions, in order to maintain grid stability and efficiency.

3. Power Management Controllers

3.1 Conventional Sliding Mode Controller (SMC)

The Sliding Mode Control algorithm is chosen for its ability to optimally operate under dynamically varying external disturbance conditions in HEMC, specifically addressing the robustness to external disturbances.

The selection of the sliding surfaces *Ψ,* σ, *Φ*, and μ is made to regulate the parameters of PV energy, wind energy SC and grid power conversion system, respectively, as shown in equation (1):

$$\psi = \frac{\partial P_{PV}}{\partial t}, \sigma = \frac{\partial Pwind}{\partial t}, \Phi = \frac{\partial P_{sc}}{\partial t}, \mu = \frac{\partial P_{grid}}{\partial t} = \frac{\partial s}{\partial t} \quad (1)$$

where $P_{PV,}$ P_{wind}, P_{sc}, and P_{grid} are the Power Sources of the grid which integrates hybrid renewable energy system.

The PV power (P_{pv}), wind power (P_{Wind}) SC power (P_{sc}) and grid power (P_{grid}) are found as:

$$P_{pv} = V_{pv} I_{pv}, P_{Wind} = V_{Wind} I_{Wind},$$
$$P_{SC} = V_{SC} I_{SC} \quad \text{and} \quad (2)$$
$$P_{Grid} = V_{Grid} I_{Grid} = P_{Source}$$

Based on equation (2), the sliding surface of the system is presented in equations (3) and (4):

$$\frac{\partial P_{source}}{\partial I_{source}} = V_{Source} + I_{Source} \frac{\partial V_{Source}}{\partial I_{Source}} \quad (3)$$

$$s = V_{source} + I_{source} \frac{\partial V_{source}}{\partial I_{source}} \quad (4)$$

where Ψ, σ, Φ, μ are the sliding surfaces of PV energy, wind energy, SC and grid, respectively, while *s* represents the total of the sliding surfaces of power sources.

The control parameter of the SMC is obtained from equations (1) - (4). SMC's distinctive duty cycle (*d*) is shown in equation (5):

$$d = v + ksign\ (s) \quad (5)$$

where *v* is the equivalent control value, calculated using equation (6) and *k* is the gain constant, therefore:

$$v = 1 - \frac{Vsource}{V_{dc}} \quad (6)$$

Duty cycle variation ranges from 0 to 1. Hence, equation (7) reveals the limitations of SMC's logic:

$$d = \begin{cases} 1\ v_{Source} + ksign\ (s) > 0 \\ 0 v_{Source} + ksign\ (s) < 0 \end{cases}, \quad (7)$$

The SMC controller finds the optimal operating point of the surface, compares it with common DC bus voltage and produces the control signal named as Modulation Index (MI). After that, the Pulse Width Modulation (PWM) signal employs a comparator to generate a control pulse operating at a frequency of 3000 kHz and a damping factor of 1200, to manage the renewable power conversion system.

3.2 SFLA Controller

The Shuffled Frog Leaping Algorithm (SFLA) is a recently proposed evolutionary algorithm which works based on the principle of the frogs searching for the maximum food source location in a waterhole, where they can jump over numerous distinct stones in search of food. Individual frogs are permitted to speak with one another, in order to fulfil the information-sharing goal, and benefit from the experiences of others, in order to improve their own leaping direction and step size. The frog population is divided into multiple memeplexes with the same number, but varying ability, to form a tiny group in a local range, enabling them to locate food efficiently and precisely. The aristocracy established in the area leads others on their own food searches among various routes. Each memeplex shuffles to exchange information with other memeplexes after a predetermined number of searches, which causes a large number of frogs to pick up new concepts from various memeplexes and recognise the social exchange of knowledge, enabling the entire frog population to effectively and swiftly locate the food source in accordance with the proper direction.

Step 1. Random generation creates a virtual population of F distinct frogs in the feasible D-dimensional space. A candidate solution to an optimization issue is represented by each frog, and the number of proposal variables is D. Thus, the vector which expresses the frog is $X_i = [X_{i1}, X_{i2}, \ldots, X_{iN}]$. Every frog has a corresponding fitness value that indicates how well the frog is performing.

Step 2. The population is divided into "m" memplexes (communities) each containing "n" frogs, so that all frogs are sorted in descending order based on their fitness ratings.

The SFLA metaheuristic describes optimization in an iterative manner. In this work, the optimal operational point for the climatic deficiency, the values of the solar irradiance, wind velocity and grid voltage are formulated and derived in the first stage, by utilizing the SFLA method, which is comprises. *D* represents the proposed variable in the memetic vector, to perform the local search. The different types of frogs, with various classes, are called Memeplex. The number of memeplex m=N/n, where *N* is the total number of frogs, and *n* is the quantity of frogs that each memeplex uses in order to select a better fitness value and to establish a higher probability regarding the existence of frogs in submemeplex. SFLA is a crucial tool for optimizing power management in systems involving PV power, wind power, SC power and grid power. It harmonizes energy utilization and regulates energy storage within super capacitors, enhancing sustainability and performance. The optimal operational point of the correspondence between the frog and its performance is defined as f_i. The frogs that perform the best and worst are determined as (X_b) and (X_w) in each memeplex, respectively, as well as best (X_g), in the entire population. The evaluation updated equations are shown below:

$$D_i = Rand \times (X_b - X_w) \tag{8}$$

$$X_w^{new} = X_w^{old} + D_i (D_{i\min} \le D_i \le D_{i\max}) \tag{9}$$

where D_i is the position of the frogs, Rand is the random value between 0 and 1, and $D_{i\,\min}$ and $D_{i\,\max}$ are permitted frog's position of lower and upper bound of the step size, respectively. In memeplex's progression, the frog X_w leaps in the direction of the frog X_b, which is updated in accordance with equations 8 and 9. This procedure is called the shuffling process. This produces the individual's desired optimal operational fit values which provide the best possible control reference parameter.

3.3 SMC-ANN Controller

An ANN-based optimal intelligence fitting tool is used to solve difficult problems. The HEMS can be effectively controlled using ANN. The ANN control consists of three layers: input, hidden, and output. This task involves gathering 2000 input and output data from the SMC-HEMC controller and using the ANN fitting tool to train it. The root mean square error represents the output performance.

3.4 Proposed SFLA-ANN Controller

The hybrid SFLA-ANN controller is a powerful combination tool used to control and optimize the nonlinear responses of hybrid renewable system. SFLA works based on ANN expert knowledge structures.

SFLA-ANN control model is developed from MATLAB "annfitting" tool trained process, as shown in Figure 3.

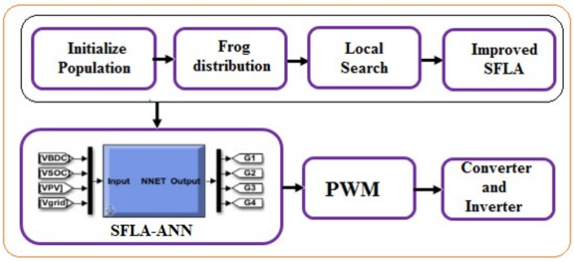

Figure 3. SFLA-ANN hybrid controller

As reference, voltage and current are considered the input parameters and the control signal of MI is considered the output parameter. It comprises the 3000 data collected from SFLA simulation models of PV, wind, SC and grid energy of the proposed system. The developed SFLA – ANN has been exported to the proposed simulation model for optimal operation of the grid. It integrates hybrid renewable energy system under RL load conditions. Solar PV and wind power are the primary sources in renewable energy, whereas the backup storage device of SC and supportive elements of controlled grid are connected to the DC switch. The developed Simulink is used to check the validity of control algorithms of SMC, SFLA, SMC-ANN, and SFLA-ANN controllers, to regulate the DC/AC conversion inverter with a dynamically changing RL load as well as the DC bus voltage. The proposed simulation model can be seen in Figure 4.

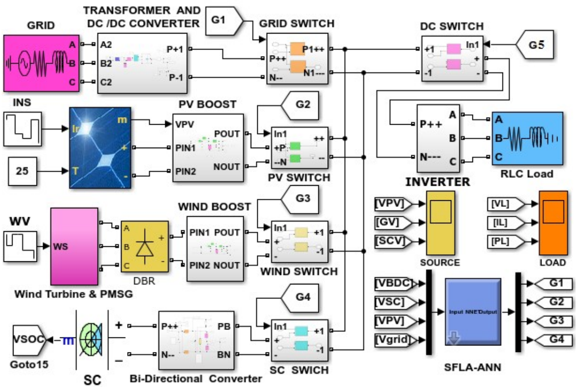

Figure 4. Proposed simulation model

The HEMC model produces four control signals which are S_{pv}, S_{wind}, S_{sc} and S_{grid} from four input parameters of the solar, wind, SC and grid energy. The PMS (see Figure 2 from the previous section) is based on five different modes, wherein the load power and the balance are delivered in accordance with equation (10):

$$P_{load}(t) \pm S_{sc} \times P_{sc}(t) = P_{pv}(t) \times S_{pv} + P_{wind}(t) \times S_{wind} + P_{grid}(t) \times S_{grid} \tag{10}$$

when $P_{RES+grid}$ > Load, the SC is charging, when $P_{RES+grid}$ < Load, the SC is discharging:

where S_{pv} S_{wind}: S_{sc} and S_{grid} are control signals of PV, wind, SC and grid energy, respectively, P is the power across the load, SC, PV, wind and grid energy with respect to time and $P_{RES+grid}$ is the total power from renewable sources and grid. The simulation is carried out for the two different conditions as follows:

(1) Static load condition;

(2) Dynamic load condition.

To test the efficacy of the suggested simulation for hybrid energy structure, the simulation is carried out with five different time configurations and it has been performed from 0s to 0.9s. Figure 5 display the source parameter for each main component in the simulation, including PV insolation, wind energy, SC voltage, SC current and SOC. The differential power sources are used to meet the load profile according to the operating condition. During periods of peak load demand, all available power sources from solar, wind, grid, and SC are used to meet load demands.

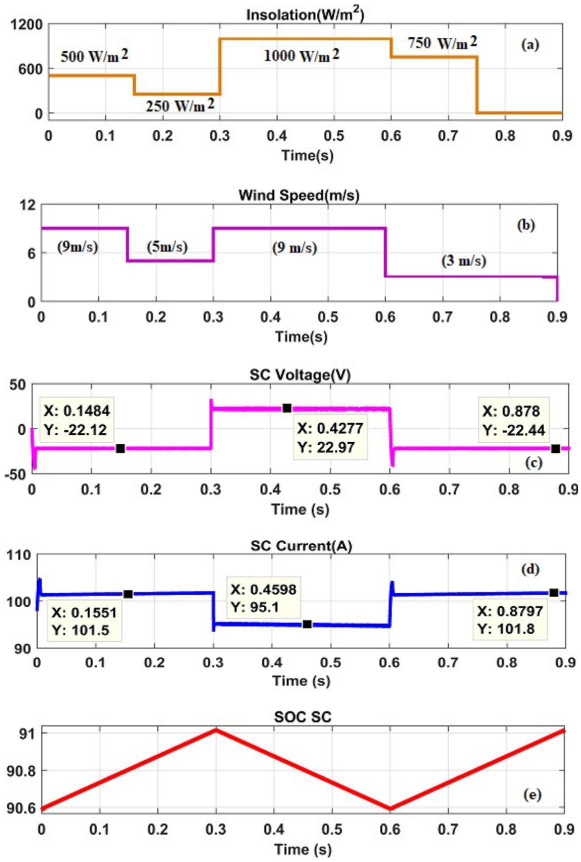

Figure 5. Source parameter (a) PV insolation, (b) wind velocity, (c) SC voltage, (d) SC current, (e) SC-SOC

3.5 Mode of Operation with Respect to Time (t) in Seconds (s)

Mode 1 *(0.0s <t< 0.15s)*: With an interval duration from 0.0s to 0.15s, PV, wind and grid energy are connected with load. In this setting of operation, the PV irradiation is 500W/m², the wind speed is 9 m/s, and the grid voltage is 750V. Therefore, within this mode, the SC starts charging.

Mode 2 *(0.15s <t< 0.3s)*: With an interval duration from 0.15s to 0.3s, PV, wind and grid energy are connected with load. In this position, the PV irradiation is 250 W/m², the wind speed is 5 m/s and the grid voltage is 750V. With this setup, the SC continues to be in the charging mode.

Mode 3 *(0.3s <t< 0.6s)*: With an interval duration from 0.3s to 0.6s, the grid voltage is isolated. At this time, both PV irradiation and wind velocity are raised to 1000W/m² and 9m/s, respectively. Further, the SC initiates to discharge.

Mode 4 *(0.6s <t< 0.75s)*: In this fixture, the grid remains isolated, the PV irradiance is 750W/m² and the wind velocity is 3 m/s. In this situation, SC is connected to charge mode.

Mode 5 *(0.75s <t< 0.9s)*: With an interval duration from 0.75s to 0.9s, the grid is reconnected to750 $V_{dc,}$ the PV irradiance is 750 W/m^2, and the wind velocity is 3 m/s. SC is still in the charge mode.

4. Experimental Results

4.1 Static Load

In order to determine the output response control using these four algorithms, the continuous RL load of (7.5kW+7.5kvar) is connected across VSI of the hybrid system with two distinct combinations of renewable sources, SC and grid, with durations ranging from 0s to 0.9s. The output voltages for integrated renewable sources, SC, and grid from the recommended DC-DC converters are shown in Figure 6, before utilizing any controllers.

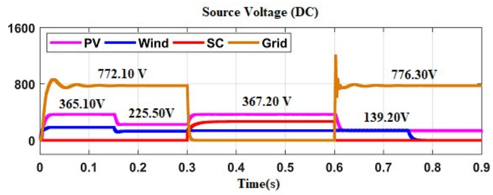

Figure 6. Source voltage (V)

Figures 7 (a) and (b) show the control signals from both suggested and traditional controllers and the zoomed-in view of Modulation Index (MI), produced by the HEMC model in accordance with the load demand and available renewable power source.

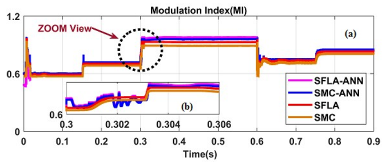

Figure 7. (a) MI (b) Zoomed-in view of MI

Figures 8 (a) and (b) present the three-phase load voltage and load current.

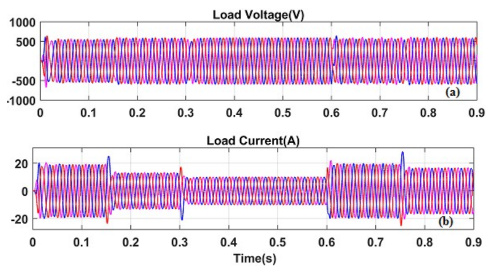

Figure 8. Three phase (a) load voltage (b) load current

Figures 9 (a), (b) and (c) present the comparison between experimental results for voltage, current and power from proposed HEMC which is connected with static RL load, this power being managed by four distinct algorithms.

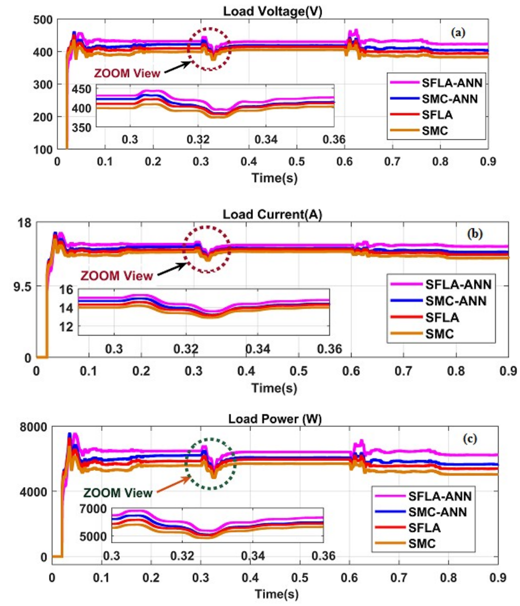

Figure 9. Comparison of static load (a) voltage, (b) current, (c) power

During the renewable sources change in static RL load, the following observations have been recorded. The respective RMS voltage is seen in Figure 9(a), and as a result, the suggested SFLA-ANN controller's upwelling load voltage ranges from 0 to 457.90V and settles at 434.8V in 0.094 seconds, whereas load voltage of SMC-ANN controller got increased from 0 to 458.7V and settled at 412.0V, in 0.10 s. Similarly, the SFLA has a transient voltage of 448.9V and a stable voltage of 403.6V with a 0.15s settling period, whereas the SMC has a transient voltage of 428.5V and a stable voltage of 392.60V with a 0.18s settling period. All the parameters have been recorded at the simulation time of 0s to 0.15s. The performances of all configuration varied from 0s to 0.9s.

The RMS current is seen in Figure 9(b), and as a result, the suggested SFLA-ANN controller's upwelling load current ranges from 0 to 16.4A and settles at 15.02A in 0.075s, whereas load current of SMC-ANN controller got increased from 0A to 16.35A and settled at 14.33A, in 0.8s. Similarly, the SFLA has a transient current of 16.03A and a stable current of 14.14A, with a 0.15s settling period, whereas the SMC has a transient current of 15.6A and a stable current of 13.61A with a 0.18s settling period. All the parameters have been recorded at the simulation time of 0s to 0.15s. The performances of all configurations varied from 0s to 0.9s.

The RMS load power is seen in Figure 9(c), and as a result, the suggested SFLA-ANN controller's upwelling load power ranges from 0 to 7437 W and settles at 6523 W in 0.09s, whereas load power of SMC-ANN controller got increased from 0 to 7533W and settled at 6001W, in 0.13s. Similarly, the SFLA has a transient power of 7192 W and a stable power of 5685 W with a 0.16s settling period, whereas the SMC has a transient power of 6665W and a stable power of 5356W with a 0.19s settling period. All the parameters have been recorded at the simulation time of 0 to 0.15s. The performances of all configurations varied from 0s to 0.9s.

4.2 Dynamic Load

During the renewable sources as well as load changes in dynamic load, the RL dynamically provided different values of specified intervals with different operating climatic conditions, coupled with varied grid voltage and observed transients of voltage, current and power.

Figures 10 (a) and (b) illustrate the modulation index (MI) for dynamic load and its zoomed-in view, respectively, generated by the HEMC model based on the available renewable power source and load demand. The following observations were made when the dynamic RL load was changing. The proposed SFLA-ANN controller's upwelling load voltage spans from 0 to 423.6V and settles at 419.3V in 0.073s, as a result of the respective RMS voltage, which is shown in Figure 11(a). In contrast, the SMC-ANN controller's load voltage climbed from 0 to 412 V before stabilizing at 405.3V in 0.09s. Comparably, the SFLA has a 399.4V steady voltage and a 405V transient voltage with a 0.14s settling time. All of the parameters have been obtained during the simulation time of 0 to 0.15s, despite the SMC having a transient voltage of 382V and a stable voltage of 350V with a 0.16s settling period. Every configuration's performance ranged from 0 to 0.9s.

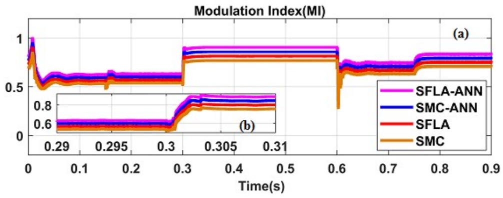

Figure 10. (a) MI, (b) Zoomed-in view of MI

The following observations was made during the load shift in the dynamic RL load. Figure 11(b) shows the respective RMS load current. As a result, the upwelling load current of the recommended SFLA-ANN controller varies from 0 to 16.97A and settles at 15.05A in 0.07s, whereas, the load current of the SMC-ANN controller increased from 0 to 14.82A and resting at 14.03A in 0.09 s. In similar fashion, the SFLA exhibits a transient load current of 14.56A and a stable load current of 13.97A with a settling time of 0.10s, while the SMC exhibits a transient load current of 14.01A and a stable load current of 13.27A with a settling period of 0.13s. All parameters were recorded during the simulation time of 0 to 0.1 seconds over the simulation period, which ranges from 0 to 0.15 seconds. Every configuration's performance ranged from 0 to 0.9 seconds. From Figure 11(c), the following numerical and simulated findings can be observed: the power output of the various dynamic load configurations for RL duration of 0 to 0.9 seconds, and the load connected with (7.5kW+7.5kvar).

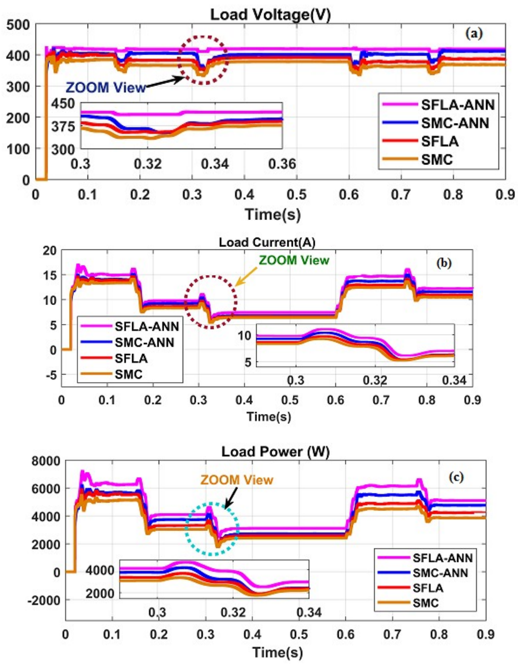

Figure 11. Comparison of dynamic load voltage (b) current (c) power

The following observations were made during the load shift in the dynamic RL load. Figure 11(c) shows the RMS load power. As a result, the upwelling load power of the recommended SFLA-ANN controller varies from 0 to 7193W and settles at 6341W in 0.07 seconds. The percentage of oscillation is 1.03%, whereas, the load power of the SMC-ANN controller increased from 0 to 6149W and rested at 5644W in 0.09 second. The percentage of oscillation is 1.21%. In similar fashion, the SFLA exhibits a transient load power of 5855W and a stable load power of 5597W, with a settling time of 0.14s. The percentage of oscillation is 1.1.8%, while the SMC exhibits a transient load power of 5392W and a stable load power of 5080W, with a settling period of 0.17s. The percentage of oscillation is 1.16%. All parameters were recorded during the simulation time of 0 to 0.15s. Every configuration's performance ranged from 0 to 0.9 seconds. It can be concluded that the SFLA-ANN's power management system significantly reduces transients and thus the oscillations, which also reduces the settling time.

4.3 An Overview of the Experimental Findings and Discussions

Table 1 and 2 display the transients of load power and settling time taken from Figure 9 (c) and Figure 11 (c), respectively. Based on a comprehensive analysis of power transients and settling time using four different algorithms, the proposed SFLA-ANN method has a maximum steady state power with shorter settling time for static and dynamic loads in Mode 1, during the specified duration of 0 s - 0.15 s, respectively. The experimental data compares the performance of different methods in handling load voltage, load current, and load power under both static and dynamic configurations. The proposed SFLA-ANN method demonstrates superior performance in reducing power transients and settling time, compared to existing approaches. Thus, the transients of load power oscillation are also significantly reduced.

The percentage power oscillation for both static and dynamic load circumstances is shown in Table 3. It clearly demonstrates that the SFLA-ANN performs better because of its low

Table 1. Load power transient and settling time for static load at mode 1 in the duration of 0 s - 0.15 s

Serial No	Algorithm	Load Power in Watts (W)		Settling Time in seconds (s)
		Transient	Steady	
1	SFLA-ANN	7437	6253	0.09
2	SMC-ANN	7533	6001	0.13
3	SFLA	7192	5685	0.16
4	SMC	6665	5356	0.19

Table 2. Load power transient and settling time for dynamic load at mode 1 in the duration of 0 s - 0.15 s

Serial No	Algorithm	Load Power in Watts(W)		Settling Time in seconds (s)
		Transient	Steady	
1	SFLA-ANN	7193	6341	0.07
2	SMC-ANN	6149	5644	0.09
3	SFLA	5855	5597	0.14
4	SMC	5392	5080	0.17

Table 3. Percentage of load power oscillations

Serial No	Algorithm	Power oscillation in %	
		Static load	Dynamic load
1	SFLA-ANN	1.13	1.03
2	SMC-ANN	1.28	1.21
3	SFLA	1.35	1.18
4	SMC	1.38	1.16

oscillations. The hybrid shuffled frog leaping algorithm-artificial neural network (SFLA-ANN) controller provides a stable output. It shows significantly reduced power oscillations and quicker settling times compared to conventional models such as SMC, SFLA, and SMC-ANN. Overall, the proposed approach supports both static and dynamic load conditions across various climatic conditions. Its effectiveness stems from the characteristics of artificial neural networks, including their ability to handle nonlinear problems, generate detailed theoretical insights, and quickly adapt to new data through optimization of weights in the ANN.

5. Conclusion

In conclusion, this study systematically evaluates the performance of four distinct power management controllers in a controlled grid-integrated hybrid renewable energy management system (HEMC). The experimental outcomes, conducted under varied climatic conditions and specified configurations of renewable sources, SC and grid inputs were meticulously analyzed. The detailed examination of voltage, current, and load power transients, settling times and percentage of load power oscillations was carried out both for experimental and numerical validations, in static and dynamic load conditions. The effectiveness of the SFLA-ANN controller was reinforced. It significantly outperformed the other controllers, demonstrating its adaptability and advanced capabilities. The study recommends the incorporation of the hybrid SFLA ANN controller in future works, highlighting its potential for further advancements. Additionally, the paper underscores the ongoing benefits of integrating green energy, particularly in the context of Electric Vehicles, emphasizing the continued relevance and application of these findings in sustainable energy systems.

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