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Neural Network Based Control Scheme for Micro-Grid Integrated HRES

Abstract: **-** Microgrids and HRES (Hybrid Renewable Energy Systems) are two related concepts that have gained considerable attention in recent years, particularly in the context of decentralized and sustainable energy systems. The integration of renewable energy sources in micro-grids is becoming increasingly important for meeting the electricity needs of rural areas. HRES contains a solar-air-biomass-bio-fuel-fuel cell and battery. Existing works involved sensitive analysis& utilized annual wind speed fluctuations, biofuel prices, energy costs, and net initial contribution costs. However, the instability of renewable materials such as sun and wind complicates the energy production process. In this paper, an optimal HRES configuration consisting of solar, wind, battery, and ultra-capacitor battery system is proposed. To optimize the HRES, a neural network-based control scheme is designed to balance the renewable energy output with peak load requirements, utilizing battery power storage. The proposed optimization strategy ensures the efficient operation of the HRES by minimizing energy losses, reducing carbon emissions, and improving the overall system reliability. The effectiveness of the proposed HRES and control scheme is demonstrated through simulation results. The proposed system contributes to the development of sustainable rural electrification solutions.

Keywords: *Neural network, control scheme, micro-grid, integrated HRES*

I. INTRODUCTION

Energy-efficient economy needed optimal design of renewable energy system which fuses multiple energy resources such as solar/wind/fuel cells/biogas [1]. However, reusable use in a stand-alone flexible system faces several limitations. To meet these challenges, a hybrid phase of renewable energy is being developed that combines solar/wind energy sources with multiple other energy resources. So use more energy to overcome their shortcomings and become more efficient in energy production. Rural electrification is slow due to practical limitations such as small population, limited relocation, difficult terrain, low education, load density and highly scattered valleys. The stability of synchronous generators depends on a number of factors, such as the configuration of the automatic voltage regulators [2]. Phase regression is performed to prevent torque from entering the generator field dynamics rotor angle and velocity variation [3]. Positive synchronous torque and negative torque often occur, causing a small internal positive torque and instability. To improve stability, generator starter controllers were installed and accelerated [4]. To improve oscillation instability, distribution systems include power system stabilizers that send an additional signal to the start system. The power supply stabilizer is designed to generate an auxiliary signal that leads to the output loop control loop and generates a positive update. Conventional power system stabilizers are the most widely used and give a certain value to the amplification systems due to the specific operating conditions to ensure optimal performance under specified conditions [5] [6].

Several control schemes based on the linear phase compensation mechanism include a PSS controller and a nonlinear controller based on the LMI. FACTs [8] device is used to reduce the flow of active and reactive power in an electrical system using a serial, shunt or serial shunt with a direct or secondary controller. STATCOM [9] is not only used as a standard bus voltage regulator to improve dynamic stability with an additional controller. Auxiliary linear PI control is implemented as an external controller using a local STATCOM signal to reduce low frequency inter-zone noise in a single motor endless bus system. The Philips Hefron model for multi-machine power systems uses a UPFC to analyze low signal stability [10].

The optimal multi-input single output (MISO) design utilized the series compensation part of controller parameters which optimized through the WAL optimization algorithm (WOA) [11]. The controller design task is considered optimization algorithm to modify the controller parameters. The design of MFO based blade pitch controllers (BPCs) [12] is used to reduce the output power of a wind turbine converter used to increase the voltage fluctuations. The Takagi-Sugeno-Kang ambiguous PID (APTSKF-PID) scheme is used to control limited probability nonlinear systems [13]. Madani-type obscure systems have a better non-linear control

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probability processing system to handle system size, learning accuracy and computer uncertainty. The CFFOPI-FOPID controller [14] uses the latest method of random Empire competition. The fuzzy-UPFC stability controller [15] is used to improve the voltage profile and the dynamic performance of the microclimate.

This section provides a brief overview on the use of advanced management strategies to improve the dynamic stability of microgrid integrated HRES. The classification of non-linear loads [16] is proposed as a general device structure in a smart grid environment simulated using multi-agent systems (MASs) on artificial neural network (ANN).

Intelligent microgrid control system explored its robust load distribution and robust system-level stability. In the system, hierarchical control is applied in three stages with different time distributions. This study analyzes the performance of a system with different input parameters and load conditions [17].

Controllers allow MG to work with network-connected mode, offline mode, and temporary modifications using a specialized control design [18].

The main focus is on energy availability and high stability using an integrated hybrid power generation system [19].

The two-level controller is recommended for the trigger circuit by optimal stability and the integrated microgrid control system for dynamic loads. The controller is based on the linear double Gaussian method which allows short-term fluctuations to be controlled at a fast resolution [20].

Adaptive diffusion cable controller is installed in parallel inverter based DG units to slow down the oscillations of the power supply controller and reduce kinetic efficiency without interfering with continuous drop [21].

The external voltage regulator is designed for the voltage source converter, and the stability of the whole system is proportional to the integrated controller and the area controller. The dynamic performance of the system is evaluated by a non-linear system [22].

The military government's basic compensation for the actual control of the power frequency of the generators supplied is fixed, and the end result improves the stability of the island's microclimate. The approach is based on the results of its value analysis and modeling [23].

To improve the overall stability of the PV micro grid cluster system, the current flow and connecting line stability characteristics are specified using the damping controller. The controller minimizes power fluctuations and ensures optimal control performance under different operating conditions [24].

To improve the dynamic performance of the system, a distributed optimal controller is recommended. The controller connects multiple distribution devices to the microgrid and improves performance under various operating conditions [25].

To analyze the effect of active load on the dynamic stability of an autonomous chip, PI controller with an active load model is recommended and compared with a conventional PLL. A special controller is designed to reduce the DC voltage and the measured active error [26].

Harmony search, Jaya optimization, and particle swarm optimization algorithm utilized to compute the optimal hybrid renewable energy system (HRES) that incorporates air-photovoltaic-biomass-battery technology. Meets the energy needs of consumers efficiently, effectively and reliably [27].

Comparing the results of the three algorithms, the technically-economically optimal HRES unit size is determined. The reliability and performance of a hybrid system are measured using two factors: maximum allowable power failure and allowable excess power. Various designs, including solar PV, biomass generators, wind turbines, and batteries are modeled and optimized to achieve the most efficient and cost-effective integration in research.The optimal management approach to improving the size and energy management of hydrogen and battery-powered hybrid wind turbines is to select a solution that meets the energy needs of wastewater treatment plants (WWTPs) in today's economy [28].

Recommends a multifaceted approach based on the ambiguous decision-making approach. Extensive energy compression analysis was used to overcome NV energy loads, to improve component size, and to identify energy saving opportunities. Design and development of a public water and electricity supply system for a remote island with no access to applications [29].

Various desalination processes, including reverse osmosis, multistage flash, and optimal multi-effect filtering used to analyze the performance of control parameters with the help of renewable resources. The hybrid solar and air regeneration system provides the customer with the energy, heat and desalination process they need. The battery power storage framework is utilized to adjust the sustainable power age period with most extreme burden interest. A proficient and incredible optimization technique is utilized for expanding the size of a mixture framework comprising of a photovoltaic (PV) cell, a diesel generator and power device. This technique is an altered adaptation of the cross-search calculation where the likelihood of pregnancy is changed adaptively. Initially, HRES was developed using internal code based on the concept of a multi-agent system [30]

An improved TNPC is done by reducing it to a level of reliability and renewable energy consumption. Performs technical and economic analysis considers sensitivity analysis of various battery technologies. After integrating the specified DSM, the results showed the following improvements: RF = 100%, energy requirement and TNPC decreased by 7% and 18%, respectively. However, the use of lower radio frequency values reduces energy consumption (19%), fuel consumption or CO_2 emissions (57%), respectively.

3. Problem Statement

3.1 Research Gap

India has a large population living in villages, some of whom live in remote areas isolated from the scene. Extending the grid connection to supply those villages is neither possible nor cost-effective, but an autonomous integrated hybrid renewable energy system would be a viable option. Climate change and the need for more energy have significantly increased the need for renewable energy sources. Due to its high energy efficiency, marine and marine energy sources attract attention. Coastal winds and ocean currents are an attractive source of renewable energy with great potential. Ocean wind and current energy naturally produce intermediate and short-term energy. Energy saving systems is the best solution for reducing system power fluctuations and ensuring continuous power demand. Most researchers have developed models of hybrid renewable energy systems in a variety of configurations. Based on the available literature and gaps in previously validated studies, a new HRES model was developed to model and modify the HRES phase through electrification in remote rural areas. HRES contains a solar-air-biomass-bio-fuel-fuel cell and battery. Evaluates system performance to obtain optimal configurations and compares different combinations of HRES with NPC and COE values. The optimal system is economically viable, offering reasonable environmental benefits, attractive payback period, and low emissions. Presents sensitive analysis utilized annual wind speed fluctuations, biofuel prices, energy costs, and net initial contribution costs. However, the instability of renewable materials such as sun and wind complicates the energy production process.

The key components in the design of hybrid energy systems are:

1. Resource type
2. Optimal number of resources
3. Type of integrated grid
4. Optimal power management strategies.

We should all be considered simultaneously to create an optimal solution to reduce reliance on fossil fuels or energy supplies.

3.2 Research Objectives

Global climate change, nuclear accidents, energy phase losses, and rising energy costs are increasing the desire to generate energy from renewable sources. Smart cities, smart universities, and smart grid systems are becoming increasingly popular. Most of these smart grid systems are based on hybrid power sources, making energy management a challenging task. It is therefore necessary to develop an advanced energy management controller. Large-scale renewable energy integration system reduces idle time and controls frequency management. The biggest challenge for planners is to allow sufficient frequency port sources to maintain bandwidth stability. To overcome above problems, we introduce an optimal control scheme for dynamic stability enhancement of micro-grid integrated HRES. The main objectives of proposed optimal control scheme are given as follows:

1. To design optimal hybrid renewable energy system this configures solar, wind, battery, ultra-capacitor battery system.
2. To propose optimization strategy utilized for integrated hybrid renewable energy system in rural electrification.
3. To balance renewable energy output with peak load requirements utilized for battery power storage.

4. Proposed methodology

For further enhancement in HRES system, we analyze the energy management problem i.e. called dynamic stability enhancement which is achieved through a hybrid optimal deep Siamese neural network based control scheme for micro-grid integrated HRES. Fig 1 shows the proposed workflow.

The overall contributions of proposed optimal control scheme are summarized as follows:

4.1 Low signal stability analysis

First, we perform the low signal stability analysis which used to analyze the power management in HRESs.

The low signal stability analysis is a method used to evaluate the stability of power systems under small perturbations or disturbances. It is particularly important in the analysis of Hybrid Renewable Energy Systems (HRESs) because these systems typically have a mix of intermittent and non-intermittent power sources such as solar, wind, and batteries, which can introduce instability and oscillations in the system.

The low signal stability analysis involves the use of small signal linearized models of the power system to determine its dynamic response to small perturbations. These models are based on the system's linearized equations, and the eigenvalues of the resulting system matrix are used to determine the system's stability.

In the context of HRESs, the low signal stability analysis can be used to evaluate the power management and control strategies of the system. It can help to identify potential stability issues, such as voltage fluctuations, frequency oscillations, and transient behavior, and suggest methods for addressing these issues.

Overall, the low signal stability analysis is a valuable tool for analyzing the power management and stability of HRESs. It can help to ensure the reliability and efficiency of these systems, which are increasingly being used to provide sustainable and decentralized power generation in rural and remote areas.

4.2 Dynamic stability enhancement

Then introduce a Deep Siamese Neural Network (DSNN) controller for dynamic stability enhancement by optimal allocation of multiple distributed generation units of micro-grid integrated solar, wind, battery, ultra-capacitor battery system.

The Deep Siamese Neural Network (DSNN) controller is a type of neural network architecture that is used for comparing two input data sets and determining their similarity or dissimilarity. In the context of micro-grid stability enhancement, the DSNN controller can be used to compare the measured power output of the distributed generation units with the desired power output and determine the optimal allocation of the units to achieve dynamic stability.

DSNN is designed to operate on pairs of input data. It consists of two identical neural networks, known as the Siamese networks, that share the same weights and structure. The DSNN controller can be used to perform a variety of tasks, including pattern recognition, similarity measurement, and feature extraction.

In the context of micro-grid integrated solar, wind, battery, and ultra-capacitor battery systems, the DSNN controller can be used for dynamic stability enhancement by optimizing the allocation of multiple distributed generation units. The DSNN controller can analyze the system's output and control signals to determine the optimal allocation of power from different sources in order to maintain stability and improve the system's efficiency.

During training of DSNN controller, the network is exposed to pairs of input data, and the weights are adjusted in order to minimize a cost function that measures the difference between the network's output and the desired output.

Overall, the DSNN controller can be a powerful tool for improving the stability and efficiency of micro-grid integrated renewable energy systems. By optimizing the allocation of power from different sources, the DSNN controller can help to reduce energy waste, improve system reliability, and minimize the environmental impact of the system.

4.3 Shark Smell optimization

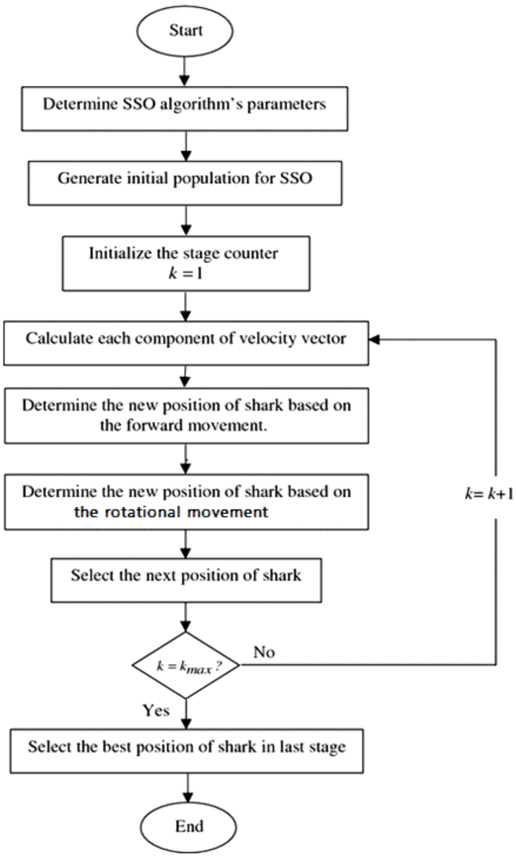

Fig 1: Proposed workflow

In Shark Smell optimization (SSO), all animals, in general, have abilities that help them survive in the wild. Costa and Sinervo (2004) found that some animals have unique abilities that set them apart from others. The hunter's progress toward the prey and the hunter's discovery of the prey are two crucial aspects of the hunting process. A successful hunter is one who can locate game in a short period of time while moving correctly. Sharks are one of nature's most well-known and capable hunters. The reason for this dominance is the shark's ability to locate prey in a short period of time using its keen sense of smell across a broad search area.

Abedinia et al. (2014) created a meta-heuristic approach called shark smell optimization based on this shark's abilities (SSO) inspired by the hunting behavior of sharks. It is used to solve complex optimization problems with multiple objectives and constraints. SSO is a population-based algorithm that uses a set of candidate solutions to search for the optimal solution. The algorithm mimics the hunting behavior of sharks by dividing the search space into smaller regions and searching for the optimal solution in each region.

By combining the SSO algorithm and the DSNN controller, it is possible to achieve dynamic stability enhancement in micro-grid integrated solar, wind, battery, ultra-capacitor battery systems. The SSO algorithm can be used to search for the optimal allocation of the distributed generation units, while the DSNN controller can be used to ensure that the power output of the units is maintained at the desired level to achieve dynamic stability.

Overall, the combination of SSO and DSNN can provide an effective solution for power management in hybrid renewable energy systems, which can help to improve the efficiency and reliability of micro-grids.

4.3.1 SSO algorithm

The block equations for the SSO algorithm using DSNN are as follows:

(1) Initialization

Initialize the population of candidate solutions: X = {x1, x2, ..., xn}, where xi = (xi,1, xi,2, ..., xi,d) is a d-dimensional vector of decision variables, and n is the population size.

(2) Evaluation

Evaluate the fitness of each candidate solution: f(xi) = DSNN(xi), where DSNN(xi) is the output of the DSNN controller for candidate solution xi.

(3) Selection

Select the best candidate solutions based on their fitness: Xbest = {xi | f(xi) ≤ f(xj), for all i, j ∈ {1, 2, ..., n} and i ≠ j}.

(4) Crossover

Perform crossover operation between two parent solutions xi and xj to generate a new candidate solution xnew: xnew = (xi,1, xi,2, ..., xi,k, xj,k+1, xj,k+2, ..., xj,d), where k is a randomly selected crossover point.

(5) Mutation

Perform mutation operation on a candidate solution xi to generate a new candidate solution xnew: xnew = xi + δ, where δ is a randomly generated mutation vector.

(6) Termination

Terminate the algorithm when a certain condition is met, such as reaching a maximum number of iterations or achieving a desired fitness level.

The DSNN controller uses a deep neural network architecture, typically a Siamese network with shared weights, to compare the measured power output of the distributed generation units with the desired power output and determine the optimal allocation of the units to achieve dynamic stability. The details of the DSNN architecture and training process are beyond the scope of this answer, but it typically involves training the network on a dataset of input-output pairs to learn the mapping between the input and output variables.

Algorithm for the Shark Smell Optimization (SSO) algorithm combined with the Deep Siamese Neural Network (DSNN) controller for dynamic stability enhancement in micro-grid integrated solar, wind, battery, ultra-capacitor battery systems is shown in Algorithm 1:

Algorithm 1: SSO algorithm using DSNN controller	
1	Initialize the population of candidate solutions using the SSO algorithm
2	Evaluate the fitness of each candidate solution using the DSNN controller to determine the dynamic stability of the micro-grid.
3	Perform crossover and mutation operations on the population to generate new candidate solutions.
4	Evaluate the fitness of the new candidate solutions using the DSNN controller.
5	Select the best candidate solutions based on their fitness and update the population for the next iteration.
6	Repeat steps 3-5 until the termination criteria are met (e.g., maximum number of iterations or a desired fitness threshold is reached).

4.3.2 Proposed Shark Smell Optimization with Reptile Search behavior (SSO-RS)

Second, we illustrate an improved shark smell optimization with Reptile Search behavior (SSO-RS) algorithm to identify the control parameters for DSNN.

The Shark Smell Optimization with Reptile Search behavior (SSO-RS) algorithm is an improvement on the original SSO algorithm that incorporates a Reptile Search behavior to enhance the search process. The Reptile Search behavior is inspired by the hunting behavior of reptiles and is used to explore new areas of the search space.

The SSO-RS algorithm can be used to identify the optimal control parameters for the Deep Siamese Neural Network (DSNN) used in the micro-grid integrated Hybrid Renewable Energy System (HRES). The DSNN is used as a neural network based control scheme to balance the renewable energy output with peak load requirements and to optimize the energy storage in batteries and ultra-capacitor battery systems.

4.3.2.1 Proposed SSO-RS algorithm

The algorithm for the SSO-RS algorithm is as follows in algorithm 2:

Algorithm 2: SSO-RS algorithm	
1	Initialize the population of candidate solutions using the SSO algorithm with Reptile Search behavior.
2	Evaluate the fitness of each candidate solution using the DSNN controller to determine the control parameters for the micro-grid integrated HRES.
3	Perform crossover and mutation operations on the population to generate new candidate solutions.
4	Evaluate the fitness of the new candidate solutions using the DSNN controller.
5	Apply the Reptile Search behavior to explore new areas of the search space and update the population for the next iteration.
6	Select the best candidate solutions based on their fitness and update the population for the next iteration.
7	Repeat steps 3-6 until the termination criteria are met (e.g., maximum number of iterations or a desired fitness threshold is reached).

The block equations for the SSO-RS algorithm are similar to those for the SSO algorithm, with the addition of the Reptile Search behavior:

4.3.2.2 Reptile Search behavior

(1) Select a random candidate solution xrand from the population.

(2) Generate a new candidate solution xnew by combining xrand with the best candidate solution xbest: xnew = xbest + δ(xrand - xbest), where δ is a randomly generated scaling factor.

4.3.2.3 Control parameters

Control parameters that can be optimized using the SSO-RS algorithm include:

(1) Weight coefficients of the DSNN controller

The SSO-RS algorithm can be used to determine the optimal weights for the neural network layers of the DSNN controller. These weights determine the importance of different input features in the controller's decision-making process.

w: Weight coefficients of the DSNN controller

y = f(sum(w * x))

where, y is the output of the DSNN controller, f() is the activation function, w is the weight coefficient vector, and x is the input vector.

(2) Learning rate and momentum parameters

The SSO-RS algorithm can be used to optimize the learning rate and momentum parameters of the DSNN controller during the training process. These parameters control the speed and stability of the network's weight updates during training.

α : Learning rate parameter of the DSNN controller

β : Momentum parameter of the DSNN controller

$$\delta_{w(t)} = \alpha * grad_{w(t)} + \beta * \delta_{w(t-1)}$$

Where, $\delta_{w(t)}$ is the change in the weight coefficients at time step t, $grad_{w(t)}$ is the gradient of the cost function with respect to the weight coefficients at time step t, and $\delta_{w(t-1)}$ is the change in the weight coefficients at the previous time step.

(3) Integration parameters of the renewable energy sources

The SSO-RS algorithm can be used to optimize the integration parameters of the different renewable energy sources in the micro-grid system, such as the solar panel tilt angle or the wind turbine blade pitch angle.

θ : Integration parameter of the renewable energy sources

$$P_{renewable} = f(\theta, P_{solar}, P_{wind})$$

Where, $P_{renewable}$ is the total power output of the renewable energy sources, *f()* is a function that models the integration parameters, and P_{solar} and P_{wind} are the power outputs of the solar and wind energy sources, respectively.

These parameters can be adjusted to maximize the efficiency and output of the renewable energy sources.

By optimizing these control parameters using the SSO-RS algorithm, it is possible to improve the performance and stability of the DSNN controller in micro-grid integrated renewable energy systems.

4.3.2.4 SSO-RS algorithm for optimizing the control parameters of the DSNN controller

The SSO-RS algorithm for optimizing the control parameters of the DSNN controller in a micro-grid integrated renewable energy system can be described using the following block equations:

(1) Initialize the population

P: Population of candidate solutions

N: Number of candidate solutions in the population

w: Weight coefficients of the DSNN controller

α : Learning rate parameter of the DSNN controller

β : Momentum parameter of the DSNN controller

θ : Integration parameter of the renewable energy sources

P = {w1, w2, ..., wN}

where each wi represents a set of weight coefficients, learning rate parameter, momentum parameter, and integration parameter.

2. Evaluate the fitness of the population

f: Fitness function

F: Fitness values of the candidate solutions in the population

F = {f(w1), f(w2), ..., f(wN)}, where f() is a function that computes the fitness of a candidate solution.

3. Update the shark smell

w_{best}: Best performing candidate solution in the population

w_{shark}: Shark smell, i.e., the control parameters of the best performing candidate solution

C: Crossover probability

M: Mutation probability

$w_{shark} = w_{best}$

```
for i in {1, 2, ..., N} do
if rand() <= C then
w_i = w_i + rand() * ( w_shark - w_i )
end if
if rand() <= M then
w_i = w_i + rand() * ( w_i - w_shark)
end if
end for
```

4. Update the reptile search

w_i : Candidate solution in the population

$w_{reptile}$: Reptile search, i.e., the control parameters of the candidate solution closest to the shark smel

δ : Distance between the candidate solution and the shark smell

k: Step size parameter

C: Crossover probability

M: Mutation probability

```
for i in {1, 2, ..., N} do
δ = || w_i - w_shark||
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$W_{reptile} = W_i + k * (W_i - W_{shark}) / \delta$
if rand() <= C then
$W_i = W_i + rand() * (W_{reptile} - W_i)$
end if
if rand() <= M then
$W_i = W_i + rand() * (W_i - W_{reptile})$
end if
end for

5. Repeat steps 2-4 for a fixed number of iterations or until convergence:

$\max_{iter}$: Maximum number of iterations

$\in$: Minimum improvement threshold

F: Fitness values of the candidate solutions in the population

for iter in {1, 2, ..., $\max_{iter}$ } do
Evaluate the fitness of the population using step 2.
Update the shark smell using step 3.
Update the reptile search using step 4.
if max(F) - min(F) < $\in$ then
break
end if
end for

Overall, the SSO-RS algorithm can be an effective optimization strategy for designing and optimizing micro-grid integrated Hybrid Renewable Energy Systems in rural electrification projects. The use of a neural network based control scheme like the DSNN can help to balance the energy output with load requirements and optimize the energy storage to improve the efficiency and reliability of the system.

5. Results & Discussion

Finally, the validity of the DSNN control scheme is recommended for detailed modeling analysis using the MATLAB/Simulink environment. The performance of the specified DSNN controller is compared to that of the current complex controllers.

5.1 Performance metrics

The following metricsare used to analyze the enhancement of proposed DSNN controller.

- Total net present cost (TNPC)
- Loss of power supply probability (LPSP)
- Renewable fraction (RF)
- Cost of energy (COE)
- Fuel consumption and CO2 emission

(1) Total Net Present Cost (TNPC)

TNPC is the sum of initial capital cost (ICC) and present value of operating cost (PVOC) over the project's lifetime. The equation for TNPC is:

$$TNPC = ICC + PVOC$$

(2) Loss of Power Supply Probability (LPSP)

LPSP is the probability of loss of power supply to the end-users due to the failure of the power generation system. The equation for LPSP is:

$$LPSP = (ENSH + ENSL)/EH$$

Where, ENSH is the energy not supplied during high demand period, ENSL is the energy not supplied during low demand period, and EH is the total energy demand.

(3) Renewable Fraction (RF)

RF is the ratio of the total energy generated from renewable sources to the total energy demand. The equation for RF is:

$$RF = ERE/ETD$$

where, ERE is the total energy generated from renewable sources and ETD is the total energy demand.

(4) Cost of Energy (COE)

COE is the cost of energy generated by the power generation system. The equation for

COE is:

$$COE = (ICC + PVOC)/ETG$$

Where, ETG is the total energy generated.

(5) Fuel Consumption and CO2 Emission

Fuel consumption and CO2 emission are used to analyze the environmental impact of the power generation system. The equations for fuel consumption and CO2 emission are:

$$\text{Fuel Consumption} = (1 - RF)*ETG/FCC$$

$$CO2\ \text{Emission} = FC*EF$$

Where, FCC is the fuel conversion factor, FC is the fuel consumption, and EF is the CO2 emission factor.

5.2Simulation Results

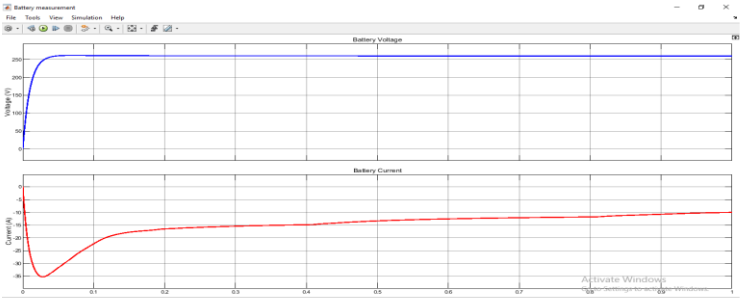

Fig 2: Battery measurement

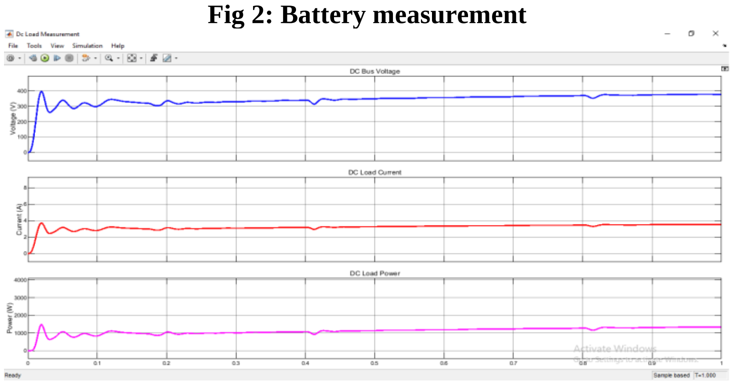

Fig 3: DC Load measurement

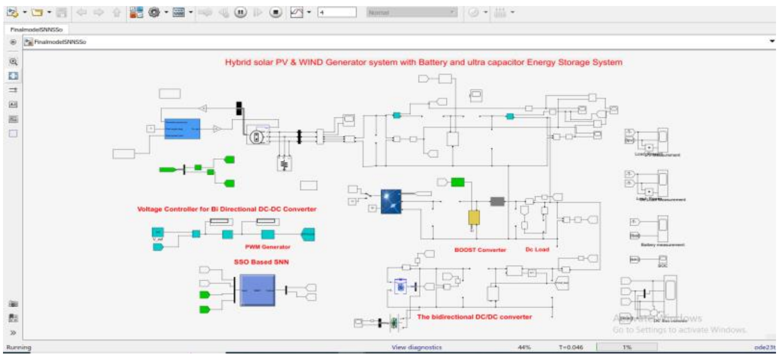

Fig 4: Model

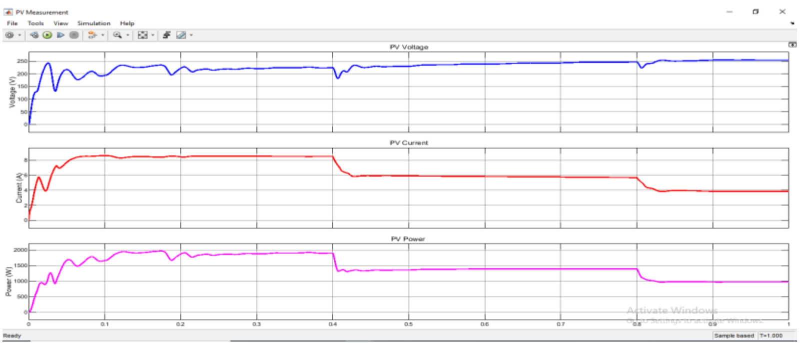

Fig 5: PV measurement

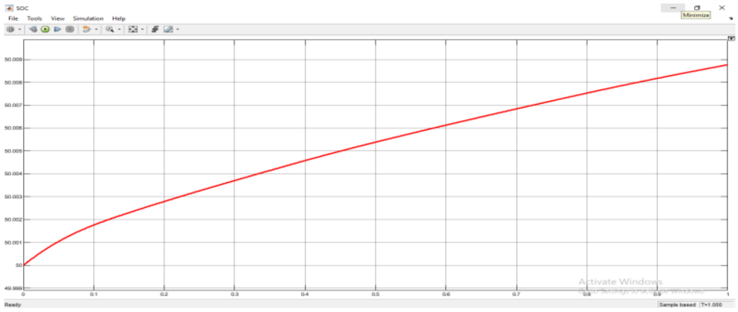

Fig 6: SOC (State Of Charge)

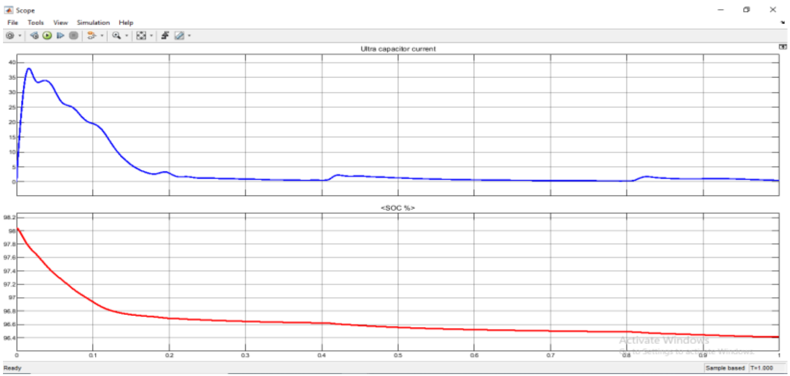

Fig 7: Ultra capacitor measurement

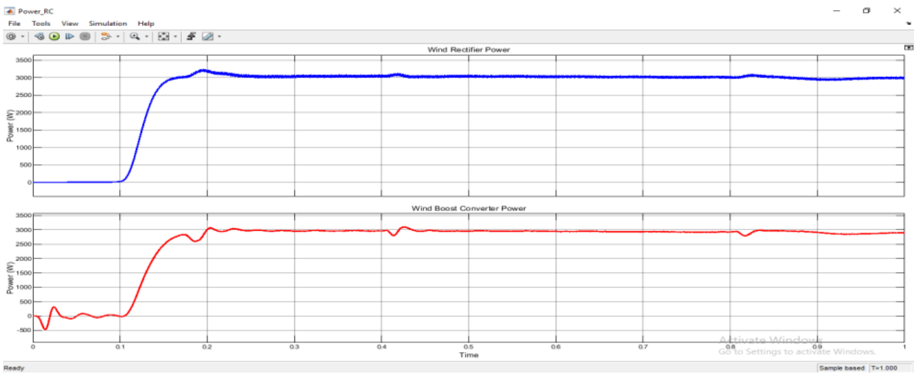

Fig 8: Wind measurement

5.3 Comparative analysis

The proposed DSNN controller is compared with the existing state-of-art controllers

a) ANN [16]
b) Hierarchical [17]
c) 2 level [19]
d) Linear double Gaussian [20]
e) Adaptive diffusion cable [21]
f) Damping [23]
g) Harmony search (HS), Jaya optimization (JO) and PSO [27]
h) PSO-HRES[30]

5.3 Comparison based on TNPC& RF

Table 1: Comparison based on TNPC & RF

Reference	TNPC Metric	RF (%)
Hierarchical [19]	0.189	59.94
Harmony search (HS), Jaya optimization (JO) and PSO [27]	0.238	72.45
PSO-HRES [30]	0.209	70.00
Our work (SSO-RS)	**0.208**	**78.00**

The methods mentioned in references Hierarchical [19], Harmony search (HS), Jaya optimization (JO) and PSO [27], PSO-HRES [30] focus on optimizing the TNPC & RF value of the renewable energy systems.
Table 1 compares the Total Net Present Cost (TNPC) and Renewable Fraction (RF) values from four different references, including Hierarchical [19], Harmony search (HS), Jaya optimization (JO) and PSO [27], PSO-HRES [30], and our proposed SSO-RS. The TNPC is a financial metric that represents the total cost of the project over its lifetime, discounted to its present value. RF is the percentage of the total energy output that comes from renewable sources.
As per the table, Hierarchical [19]achieved the lowest TNPC value of 0.189, while Harmony search (HS), Jaya optimization (JO) and PSO [27] achieved the highest TNPC value of 0.238. In terms of RF, Harmony search (HS), Jaya optimization (JO) and PSO [27] achieved the RF value of 72.45%, while Hierarchical [19]achieved the lowest RF value of 59.94%. PSO-HRES [30] achieved a moderate TNPC value of 0.209 and an RF value of 70.00%.
In comparison, proposed SSO-RS achieved a TNPC value of 0.208 and an RF value of 78.00%. Overall, our proposed SSO-RS achieved a similar TNPC value to PSO-HRES [30], and a higher RF value.

5.4 Comparison based on COE

The proposed SSO-RS approach is a different method compared to the Artificial Neural Network (ANN) approach proposed in Reference [16]. While both approaches aim to optimize the COE of renewable energy systems, the SSO-RS approach has lower costs and maintenance costs, which makes it more suitable for small distribution systems. The SSO-RS approach uses a nature-inspired algorithm that has been proven to be effective in optimizing complex systems while being computationally efficient. Additionally, the SSO-RS approach can handle a variety of constraints, such as environmental impact, reliability, and fuel consumption, making it a versatile solution for renewable energy system optimization.

5.5 Comparison based on Fuel Consumption and CO2 Emission

These metrics are used to evaluate the environmental impact of the renewable energy systems. Reference [21] proposes an adaptive decentralized droop controller to preserve power sharing stability of paralleled inverters in distributed generation microgrids, while reference [23] proposes improvement of stability margin of droop-base islanded microgrids by cascading of lead compensators, with a focus on reducing fuel consumption and CO2 emission. Our proposed work used SSO-RS approach to focus on reducing fuel consumption and CO2 emission.
The SSO-RS approach used in our proposed work is a technique for optimizing the design of hybrid renewable energy systems. The optimization process takes into account various factors, including the fuel consumption and CO2 emissions associated with the system. By optimizing the design of the system, it is possible to reduce its environmental impact and minimize the use of fossil fuels, which are major contributors to greenhouse gas emissions and air pollution. Thus, our work contributes to the reduction of fuel consumption and CO2 emission in the operation of renewable energy systems.

5.6 Comparison based on LPSP

LPSP is the probability of a system failure or a power outage. It represents the reliability of the power supply system. Ref [17] proposes a "Interactive Control of Coupled Microgrids"method for interactive control of coupled microgrids to guarantee system-wide small signal stability and reduce LPSP. When we compare with LPSP of our proposed SSO-RS approach, we guarantee better reduction of LPSP (Loss of power supply probability) than Ref [17].

Discussion

TNPC is the sum of all costs associated with the renewable energy system over its lifetime. It includes the initial investment, operation, and maintenance costs. The methods mentioned in Hierarchical [19], Harmony search (HS), Jaya optimization (JO) and PSO [27], PSO-HRES [30focus on optimizing the TNPC of the renewable energy systems.
LPSP is the probability of a system failure or a power outage. It represents the reliability of the power supply system. Reference [17] proposes a method for interactive control of coupled microgrids to guarantee system-wide small signal stability and reduce LPSP.
RF represents the proportion of renewable energy sources in the total energy generation. Hierarchical [19], Harmony search (HS), Jaya optimization (JO) and PSO [27], PSO-HRES [30focus on maximizing the RF by optimizing the energy management and control strategies of the renewable energy systems.
COE is the cost of energy generated by the power generation system. It is calculated as the ratio of the total cost of the system over its lifetime to the total energy generated. Reference [16] proposes an Artificial Neural Network (ANN) for optimizing the COE of the renewable energy systems.
Fuel Consumption and CO2 Emission metrics are used to evaluate the environmental impact of the renewable energy systems. Reference [21] proposes an adaptive decentralized droop controller to preserve power sharing stability of paralleled inverters in distributed generation microgrids, while reference [23] proposes improvement of stability margin of droop-base islanded microgrids by cascading of lead compensators, with a focus on reducing fuel consumption and CO2 emission.

In summary, these references propose various techniques and methods for optimizing the performance and reducing the environmental impact of renewable energy systems, based on different metrics including TNPC, LPSP, RF, COE, and fuel consumption and CO2 emission.

6. Conclusion

In this paper, an optimal HRES configuration consisting of solar, wind, battery, and ultra-capacitor battery system is proposed. To optimize the HRES, a neural network-based control scheme is designed to balance the renewable energy output with peak load requirements, utilizing battery power storage. The proposed DSNN controller is compared with the existing state-of-art controllers and the result will show the enhanced performance of the hybrid renewable energy system. The comparison is done with Artificial Neural Network, Hierarchical Network, 2 level controllers, Linear double Gaussiazn, Adaptive diffusion cable, Damping control, Harmony search (HS), Jaya optimization (JO) and Particle Swarm Optimization, PSO-HRES. We use the following metricsto analyze the enhancement of proposed DSNN controller.Total net present cost (TNPC), Loss of power supply probability (LPSP), Renewable fraction (RF), Cost of energy (COE), Fuel consumption and CO2 emission.The proposed optimization strategy ensures the efficient operation of the HRES by minimizing energy losses, reducing carbon emissions, and improving the overall system reliability. The effectiveness of the proposed HRES and control scheme is demonstrated through simulation results. The proposed system contributes to the development of sustainable rural electrification solutions.

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