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Hybrid Deep Learning with Bitterling Fish Optimization and Secretary Bird Optimization for Maximizing Efficiency in High Voltage Gain Interleaved Boost Converters Integrating PV and Wind Systems

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This research aims to maximizing the efficiency in high-voltage gain interleaved boost converters in PV and wind integration systems. However, there is a challenge in balancing system complexity, scalability, requiring advanced algorithms, high switching frequencies, and higher costs, to overcome this issue, a novel “Neuro-LSTM BitterSec Optimization Network (NL-BSONet)” is introduced. Power quality issues arise in boost topology due to variable sunlight and wind, challenging stability as conventional MPPT struggles with rapid transients. To solve this, a novel Adaptive Neuro-DRL Bitterling Optimizer (AN-DRLBO) is introduced, which improves energy conversion and dynamic adaptation in renewable energy with the help of Deep Reinforcement Learning (DRL) for adaptation purpose, Adaptive Neural Networks (ANN) for stabilization purpose and Bitterling Fish Optimization (BFO) for optimization purpose. Furthermore, achieving optimal parameters is challenging due to environmental variability; traditional optimization methods lack real-time adaptability, compromising stability and power output. To address this issue, a novel Adaptive LSTM-Encoded Secretary Optimization Network (AL-SONet) is introduced, which effectively manages renewable energy conditions by utilizing efficiency, stabilizing power output, and sustaining high-voltage gain interleaved boost converter performance with help of Long Short-Term Memory (LSTM) Networks for prediction purpose, Autoencoder-based Optimization (AEO) for simplification purpose, Secretary Bird Optimization (SBO) for adjustment purpose. The proposed modelenhances high voltage-gain converters with a 97% efficiency, 32.5 dB voltage gain, and low power ripple and stability for efficient

integration of renewable energy sources.
Keywords: Renewable energy integration, High-voltage gain converters, Power quality, Dynamic adaptation, Real-time optimization, Stability enhancement, Efficiency maximization, Environmental variability, Parameter tuning, Energy conversion.

1. Introduction

The increasing demand of renewable energy worldwide pertaining to photovoltaic and wind power energy's challenges researchers to have good and efficient power-converting machines, integrating these two ways into the electrical grid without the fluctuations of renewables [1, 2]. High voltage gains interleaved boost converters emerging today as the most promising solution in order to address these challenges, mainly for applications requiring high voltage transformation that still suffers from efficiency, like PV and wind hybrid energy systems. Still, however, this is a significant drawback of these converters: although they are powerful and capable of handling various input voltage ranges, efficiency must be maximized to provide consistent performance under fluctuating load conditions [3, 4].

Interleaved boost converters have been widely recognized for their benefits, through which the input current ripple is reduced, thermal performance is improved, and renewable sources may be easily integrated with high power density [5, 6]. However, design of such topologies with maximum efficiency requires many parameters including the duty cycles, inductor currents, and the output voltages, all of which may be quite sensitive to the dynamic conditions of PV and wind inputs [7]. The traditional control methods as well as linear optimization techniques often fail to capture well the nonlinear, time-variant nature of the renewable energy sources. Hybrid deep learning and bio-inspired optimization approaches are gaining popularity based on their ability to handle such complexities in order to further improve the accuracy of control mechanisms [8, 9].

In this paper, a hybrid deep learning technique allied with BFO and SBO algorithms is proposed for optimizing the efficiency of high-gain interleaved boost converters used in PV and wind-based hybrid systems. Hybrid deep learning models process enormous data volumes, predicting optimal control parameters for changes in inputs from winds and PV, in real-time [10, 11]. This is made possible by the application of bio-inspired optimization algorithms, including BFO and SBO, by which the model parameters are dynamically adjusted for maximum efficiency. BFO derived from the bitterling fish reproductive behaviour is efficient for nonlinear search spaces and fine-tunes internal model parameters. For its part, SBO derived from the hunting behaviour of a secretary bird is ideal for meta-level optimization over various operational modes [12], [13].

Combining BFO and SBO can allow a hierarchical optimization technique to be used, wherein BFO is used to optimize internal parameters of the deep learning model and SBO manages the overarching hyperparameters while changing the model according to environmental and operational needs, [14]. The hybrid system activates deep learning for predictive control, BFO for micro-scale rules adjustments, and SBO for the macro-scale optimization within those points to an efficient solution of the challenge of variability inherent in inputs from PV and wind energy. This approach therefore goes along with the recent developments in machine learning and bio-inspired algorithms which have achieved significant improvements in the efficiency of energy conversion in renewable systems [15].The objective of this research is to design an efficient control system for interleaved boost converters to optimally control input from photovoltaic and wind inputs. Specific contributions that the study makes in this work are as follows:

- Develop a hybrid deep learning model that is tailored for high-voltage gain interleaved boost converters designed to predict and adapt changes in the input renewable energy.
- Parameter-tuning via Bitterling fish optimization to allow the model to dynamically adapt to the very high speed at which both PV and wind inputs are changing.
- Using Secretary Bird Optimization to tune system-wide hyperparameters to optimize the model in terms of performance across a wide range of operating conditions.
- It demonstrates the fact that the model proposed here is much more efficient and stable compared with traditional optimization models.

The main contribution of these research is follows:

➢ The proposed AN-DRLBO updates the control parameters using DRL, ANN, and BFO to address issues of power quality due to the variable nature of solar and wind energy in real-time stabilization of voltage, reduction of transients, and maximization of power extraction.

➢ To overcome the complexity of renewable energy systems owing to environmental variability, the model AL-SONet combines LSTM for trend prediction, AEO for parameter tuning efficiency, and SBO for real-time adaptive adjustments to enhance stability and power output.

The rest of this paper follows the outline below: Section 2 recalls some related work concerning renewable energy converters and bio-inspired optimization algorithms; Section 3 lays down the proposed methodology, namely the hybrid deep learning architecture, as well as the optimization framework BFO-SBO; Section 4 details the experimental setting and results analysis together with respective metrics of evaluation; and finally Section 5 draws some conclusions and indicates future lines of development.

2. Literature Survey

Anjappa et al. [16] designed interleaved DC-DC boost converter was a high-gain system that had the ability to maximize the power output coming from PV arrays. It was an improvement of the two-phase interleaved boost converter. The technique provided significant reduction in ripple current, thereby offering efficient voltage elevation for grid integration and high-power applications and achieved remarkable 96% efficiency with a voltage boost of 25V to 400V. However, it had limitations with system complexity and cost considerations.

Algamluoli et al. [17] proposed an optimized DC-DC converter using a modified switched inductor-capacitor technique to realize ultra-high voltage gain for renewable energy systems.

Indeed, this technique reduces the voltage stress and current across the main switch, inductors, and diodes with a critical cut by boosting the efficiency of the converter up to 96.2%. The implications were the design complexity and reliance on high switching frequencies, which increase the cost of operation by requiring much higher switching energies.

Ibrahim et al. [18] introduced a two-stage MPPC based on an integration of PV, wind, and fuel cell sources along with a bidirectional battery through an isolated output port optimized by Harris Hawk's algorithm. Here again, this approach had significantly reduced issues like intermittency and improved the system's resiliency and efficiency. However, complex system design confined its applicability with the potential real-time optimization challenges and conditions under variation in CES input conditions.

Kulasekaran et al. [19] introduced an HGBC-PVS to connect low-voltage PV panels to a higher-voltage network within a DC microgrid that used Adaptive Incremental Conductance for MPPT. This resulted in effective maximization of solar power extraction for voltage gain and efficiency. There were found efficiency limitations at larger setups, hinting at cascaded converter designs as future improvement ends.

Xiao et al. [20] introduced a hybrid green ship power system based on a six-phase interleaved boost converter using fuel cells and lithium batteries with 10kW power. It featured stable current control, efficient power distribution improvement, and high quality of ripple suppression, as well as anti-interference capabilities. The design complexity and possible challenges to the real-time adjustment of currents were significant limitations in the dynamic control system.

Uzmus et al. [21] proposed a modified MPPT technique for off-grid photovoltaic systems through an interleaved hybrid DC-DC boost converter. This technique predicted the input voltage from the branch current. Consequently, this made sure of a stable output and reduced the stress of the components due to minimized ripples in the input current. Also, reduced costs are ascribed to the technique since it did not require a sensing circuit for the input voltage, which guarantees long system lifespan. However, limitations abound: it relies on prediction accuracy; its performance was adversely affected in the case of sudden and rapid power fluctuations.

Kumar et al. [22] introduced a HRES for EV charging using an HGZS converter. Here, the wind end employs a DFIG-based wind system with PI control and PV optimization using Type 2 Fuzzy MPPT. Therefore, it optimizes its energy extraction to maintain grid stability while feeding surplus energy back into the grid. Though it was an attractive solution to rely on renewable sources to meet the rising power demand, it does pose potential challenges of large-scale integration and adaptation in changing climatic conditions.

Hashemzadeh et al. [23] introduced a high-voltage gain converter using a two-winding coupled inductor and voltage multiplier cells that reduce the voltage stress of photovoltaic energy systems. The design reduces the number of components, makes control easier, and increases efficiency. Although it was effective, it was quite limited due to its single-switch configuration, which have an impact on scalability in higher power applications, and further testing was required for diverse load conditions.

Hawsawi et al. [24] introduced two DC-DC converter topologies integrated with solar PV:

conventional and a switched capacitor boost converter. It compared the MPPT performance results using P&O, INC, GA, and PSO algorithms. In the switched capacitor configuration, improved current control and voltage regulation ensured excellent dynamic loading and high stability. However, the study left much to be optimized as regards ensuring high reliability of the system with decent accuracy regarding several power peaks being tracked.

Gopalasami et al. [25] developed the DIDO DC–DC multiport converter with the hybridization of SLBC along with integrating PV and battery sources within the system. It offers high voltage gain and highly efficient power conversion with minimal losses due to conduction. The system achieved 94.8% efficiency and 1.2 kW output; however, there is still a requirement to optimize it and scale the system more for widespread applications, especially for large electric vehicle systems.

From the above study it is clear that in [16] system complexity and cost considerations, in [17] design complexity and reliance on high switching frequencies, in [18] complex system design and challenges in real-time optimization, in [19] efficiency limitations at larger setups, in [20] design complexity and real-time current adjustment challenges, in [21] prediction accuracy dependency and performance degradation in power fluctuations, in [22] challenges in large-scale integration and adaptation to changing climates, in [23] single-switch configuration impacts scalability in higher power applications, in [24] need for optimization and accuracy in tracking multiple power peaks, in [25] requires further optimization and scaling for widespread applications. Hence there is a need for novel to overcome these challenges.

3. Proposed Methodology

This research focuses on maximizing the efficiency in high-voltage gain interleaved boost converters in PV and wind integration systems, leading to better renewable energy conversion through optimized power output and stable performance. This research introduces a new approach of hybrid deep learning with Bitterling Fish Optimization (BFO) and Secretary Bird Optimization (SBO) for maximizing the efficiency gain of a high-voltage gain interleaved boost converter in PV and wind energy systems. Maximize power production ensuring firm, efficient conversion of energy through the integration of renewables, optimization in the dynamic energy conditions in which its operations take place, and increasing the system's reliability level. However, there is a major challenge to the high-voltage gain interleaved boost converter for integration of PV and wind energy is finding a balance in a way that maintains system complexity, scalability, and real-time adaptability. Complexity often found in the association with stability in high efficiency and performance introducers additional design intricacies and dependency on advanced algorithms and high switching frequencies, amounting to higher costs and making optimization difficult towards dynamic environmental conditions and variable power demands. Therefore, a novel "Neuro-LSTM BitterSec Optimization Network (NL-BSONet)"is introduced in this approach.

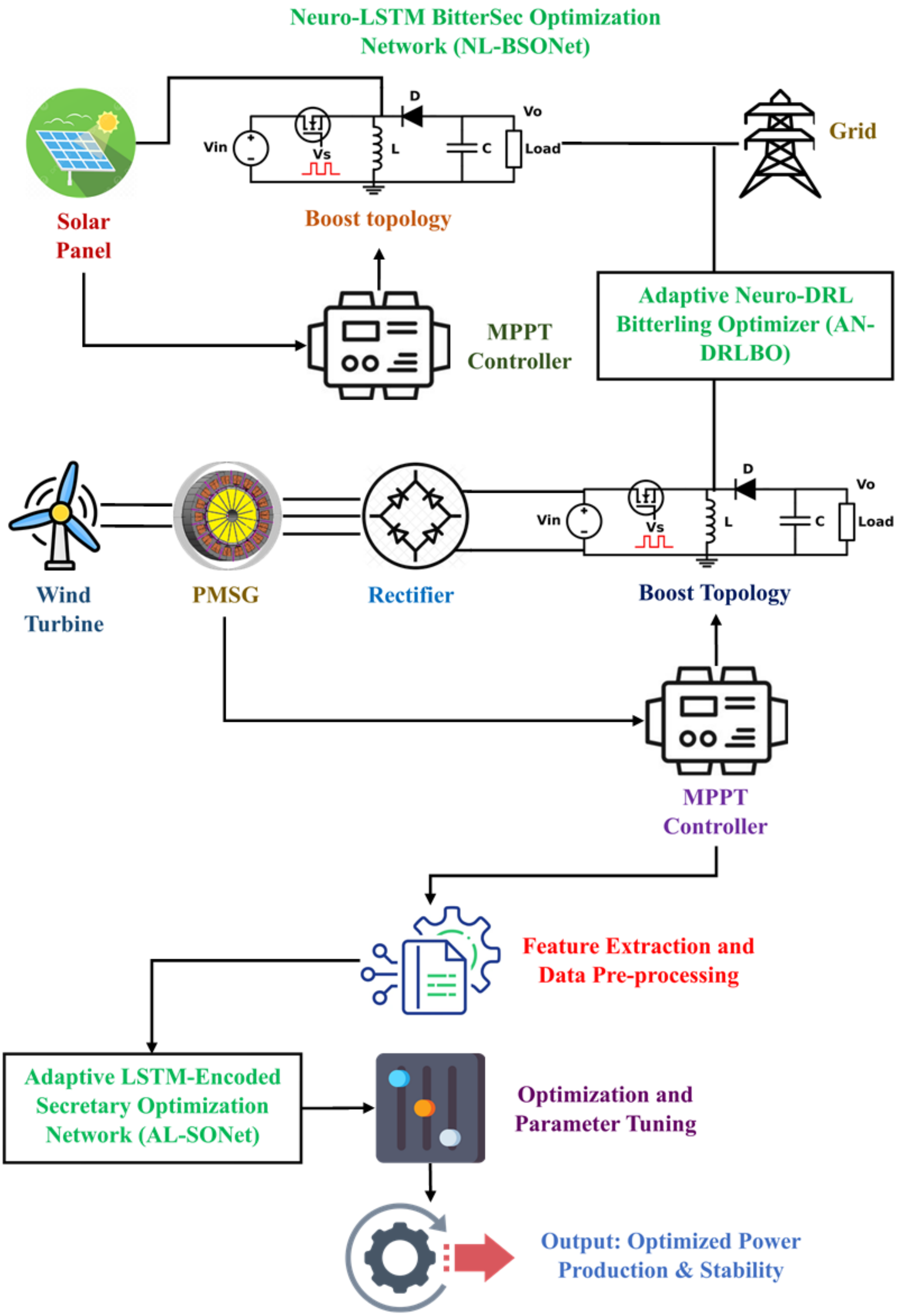

Figure 1. Architecture of the proposed NL-BSONetfor Maximizing Efficiency in High Voltage Gain Interleaved Boost Converters Integrating PV and Wind Systems

Figure 1 shows the architecture of the proposed NL-BSONet for Maximizing Efficiency in High Voltage Gain Interleaved Boost Converters Integrating PV and Wind Systems. This hybrid method of wind-Solar PV generation integrates wind and solar energy sources in the generation of renewable energy. Solar energy output is optimized with the MPPT controller and boost converter, while wind energy passes through the generator depending on the type of generator used (PMSG), rectifier, and MPPT-controlled boost converter. Each of them feeds power into the grid. The Neuro-LSTM possible optimization algorithm and AN-DRLBO are further refined from the algorithms that have been proposed in this Revised Text. The AL-SONet helps choose the optimal feature. This leads to algorithm development and tuning. Due to feature extraction and data pre-processing steps, the final output is fine-tuned to make stable power production possible during the whole run.

3.1 Data Collection and Pre-processing

It is essentially based on data from environmental sensors, such as solar irradiance, wind speed, or ambient temperature, that the behaviour of the renewable energy system is determined.

3.1.1 Data collection:

Real-time data will be collected from PV and wind energy sensors (solar irradiance sensors, anemometers, temperature sensors). Measurements of voltage and current obtained from both sources will also be recorded for inclusion in the hybrid deep learning model, thus ensuring that a comprehensive dataset is represented to capture the diverse environmental conditions.

3.1.2 Data Preprocessing:

- Normalize or standardize all sensor readings to ensure total consistency of reading across various measurements.
- Smoothing techniques (like the moving average) will be applied in order to mitigate the effects of fluctuations with respect to sunlight and wind conditions that may have rendered noise in the data collected.
- Handling of missing or erroneous sections of data will be performed in the form of interpolation or imputation.
- Labelling and segmentation of data for environmental conditions e.g., periods of high sunlight or strong winds for better training of the model.

3.2 MPPT Controller

Since it tracks the converter to find the peak power point, an MPPT (maximum power point tracking) controller is used to extract maximum power from the PV and wind systems by dynamically controlling the operating point of the converter. In this research, the MPPT controller assures that the interleaved boost converter works optimally under changing conditions. The controller optimizes the voltage and current settings, which are fluctuating because of environmental changes, aiming for the highest possible electrical power output.An MPPT equation common in photovoltaic conditions is shown in the equation (1):

$$P = V \times I \tag{1}$$

Where, P is the power output, V is the voltage, and I is the current. Adjust V and I in real time according to the MPPT algorithm, in order to output the maximum P at all times.

3.3 Adaptive Neuro-DRL Bitterling Optimizer (AN-DRLBO)

In the existing output of the boost topology where energy from the solar panels and wind turbines fed to the grid is taking place, power quality issues generally occur due to the variable nature of renewable sources by these changes' variation in sunlight or in wind speeds, which makes it challenging to stabilize. Conventional MPPT techniques, like Perturb and Observe or Incremental Conductance suffer from such rapid transients which result in poor quality power and instability.To solve this instability issue in the boost topology, a novel Adaptive Neuro-DRL Bitterling Optimizer (AN-DRLBO) is introduced,to solve several crucial issues with the implementation of high-gain interleaved boost converters, used in many renewable energy integration systems, particularly those powered by solar photovoltaic and wind energy sources.

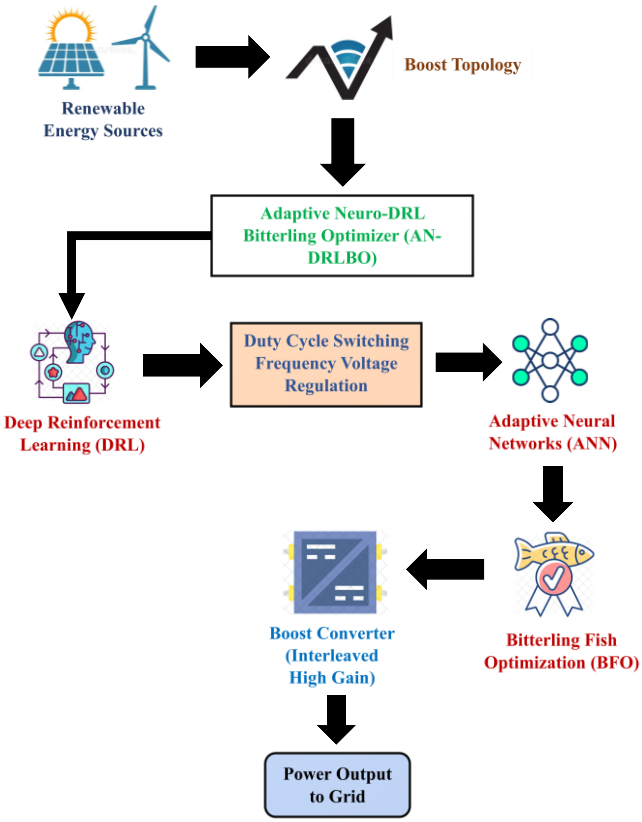

Figure 2. Architecture of the proposed AN-DRLBO

The architecture of the proposed AN-DRLBO is shown in the Figure 2. The main objective behind AN-DRLBO is to dynamically adapt to rapid transients within renewable energy systems; therefore, the key purpose is targeted at enhancing the quality and stability of the output power by exploiting the capabilities of real-time dynamic response adaptation towards changes in wind speed or sunlight that create sudden variations. AN-DRLBO thus deals with the complicated nonlinear dynamics of renewable sources by real-time optimisation of the system performance and ensuring continuous adaptation of the system to the environment along with sustaining high efficiency even with inherent variability in renewable energy sources. This is essential for large-integration PV and wind systems that must work reliably under a constantly changing set of conditions. It is the combination of Deep Reinforcement Learning (DRL), Adaptive Neural Networks (ANN) and Bitterling Fish Optimization (BFO) which is detailed in further section.

3.3.1 Deep Reinforcement Learning (DRL)

DRL is a subset of the larger category of machine learning which involves the combination of reinforcement learning and deep learning. In RL, the core problem is for an agent that is computational to learn decisions by trial and error. DRL encompasses deep learning within a solution that equips agents with the ability to make decisions from unstructured input data, without the manual engineering of a state space.

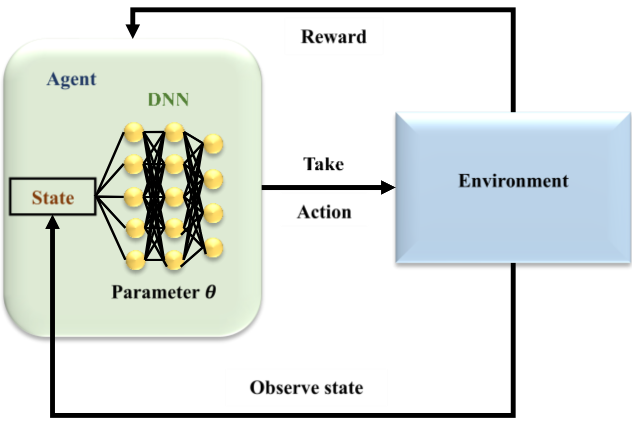

Figure 3. Structure of the DRL

Figure 3 describes the basic structure of the DRL. While DRL plays a critical role in adapting to the constantly changing environment of renewable energy systems, such as fluctuations in sunlight and wind speeds, through constant interaction with an environment and receipt of feedback in the form of rewards, it allows the system to learn optimal control strategies over time. This adaptive learning process ensures that the system is update its parameters in real time. In that case, it attains power extraction in a very efficient manner while keeping high-quality output. For this, DRL minimizes transients and enhances the stability along with overall performance, with smooth energy conversion even as environmental changes are highly rapid.A mathematical representation of the role of DRL in optimizing the power extraction and the stability of high-voltage gain interleaved boost converters in renewable energy systems will be represented by the system's state given by $s_t$represents environmental as well as system conditions at time t. This includes solar irradiance, wind speed, voltage, current, among other data specific to the system as per equation (2):

$$s_t = [I_{pv}, V_{pv}, I_{wind}, V_{wind}, P_{out}, \dots] \quad (2)$$

Where, $I_{pv}, V_{pv}$are the currents and voltages from the photovoltaic panel,$I_{wind}, V_{wind}$are the currents and voltages from the wind turbine,$P_{out}$is the output power of the converter. The action$a_t$means the decisions taken by the system such as switch the duty cycle of the boost converter or dynamically tune the control parameters as per the equation (3):

$$a_t = [D_t, \alpha_t, \dots] \tag{3}$$

Where, $D_t$represents the duty cycle of the boost converter at time$t$,$\alpha_t$represents other control parameters, such as switching frequency or voltage regulation settings. The reward function$R_t$is used to guide the learning process, rewarding the system for keeping optimal power extraction and stability and penalizing for instability or poor performance. A typical reward function is appeared as per equation (4):

$$R_t = w_1 \cdot P_{out}(t) - w_2 \cdot \left|V_{ripple}(t)\right| - w_3 \cdot \left|I_{surge}(t)\right| \tag{4}$$

Where, $P_{out}(t)$is the output power at time$t$,$V_{ripple}(t)$is the voltage ripple (indicating instability),$I_{surge}(t)$is the current surge (indicating instability),w_1, w_2, $w_3$are weighting factors that emphasize some of the objectives (e.g., greater weight for output power, lesser weight for ripples and surges). The Q-function$Q(s_t, a_t)$signifies the present expected future reward given the current state$s_t$and action a_t. In DRL, the agent tries to maximize this Q-function over time as shown in the equation (5):

$$Q(s_t, a_t) = E\left[R_t + \gamma \cdot \max_{a_{t+1}} Q(s_{t+1}, a_{t+1})\right] \tag{5}$$

Where, γ is the discount factor (between 0 and 1) which weighs up the importance of future rewards,the agent selects the action a_t that maximizes$Q(s_t, a_t)$, advancing the control parameters in order to maximize future rewards. The policy$\pi(a_t|s_t)$determines the action policy at any state. In DRL, the policy is represented by a deep neural network, and the weights of this network are updated by loss, typically with the following TD equation (6):

$$L(\theta) = E\left[\left(R_t + \gamma \cdot \max_{a_{t+1}} Q(s_{t+1}, a_{t+1}; \theta^-) - Q(s_t, a_t; \theta)\right)^2\right] \tag{6}$$

Where, θ are the weights in the Q-network (the neural network),θ^- are the weights in the target network (used for stability in training),The loss function $L(\theta)$ is the difference of the Q-values that are predicted against the target Q-values. The online adaptation of the parameters with respect to the learned policy ensures that the system could quickly adapt to changing environments. For example, the update rule for dynamic parameters of the system, such as duty cycle and switching frequency, depends on a maximum reward as per equation (7):

$$\Delta\theta_t = \eta \cdot \nabla_\theta Q(s_t, a_t; \theta) \tag{7}$$

Where,$\eta$is the learning rate,$\nabla_\theta Q(s_t, a_t; \theta)$is the gradient of the Q-function with respect to the parameters.Hence, the control parameter can be tuned in real-time, which provides an opportunity to determine sufficient extraction under the possible instantaneous alteration of environmental conditions, such as when the stability of a system does not have to be compromised.

3.3.2 Adaptive Neural Networks (ANN)

ANNs are a type of artificial neural networks, which is work under dynamic environments, learns, and adapts during the training. These networks are generally classified as having an online learning mode due to the accuracy characteristic in pattern recognition and predictions.

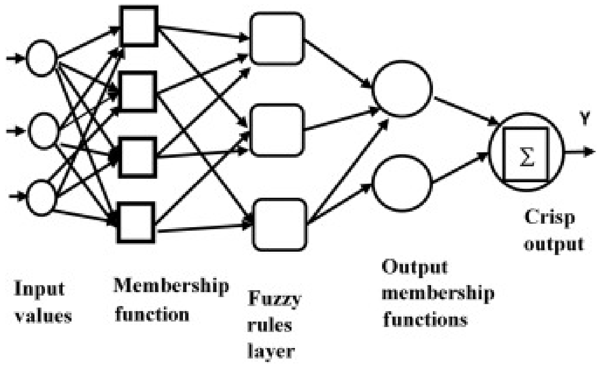

Figure 4. Structure of the ANN

The basic structure of the ANN is shown in the Figure 4. ANN, is actually set their control settings dynamically so that during power surges, the voltage will stay stable and harmonics will be minimized. They compute in real-time, which allows fast, fine-grained perturbations that cannot readily cause degradation in power quality and then stabilize the power output fed to the grid.The desired functional description is to design an ANN that controls the voltage stability dynamically and minimizes the harmonics in case of surge power. The ANN has been designed to keep the voltage V within a desired range. Let V_{ref} be the reference voltage, and V_{out} be the output voltage. The error $e(t)$between the reference and output voltage is shown in the equation (8):

$$e(t) = V_{ref} - V_{out}(t) \tag{8}$$

The ANN is trained in such a way that this error is minimized through real-time adjustments of the control parameters. For example, if the ANN generates a control signal $u(t)$, the output voltage is updated in terms as per equation (9):

$$V_{out}(t+1) = V_{out}(t) + \alpha u(t) \tag{9}$$

where α is a tuning parameter that scales the control adjustment.In order to reduce the harmonics, the ANN is also focus on the Total Harmonic Distortion (THD) of the output signal. The THD is calculated as follows in the equation (10):

$$THD = \frac{\sqrt{\sum_{n=2}^{\infty} V_n^2}}{V_1} \tag{10}$$

Where, $V_1$is the fundamental frequency component and $V_n$denotes the n^{th} harmonic component. The ANN attempts to minimize THD in the control signal $u(t)$in terms of minimizing the harmonic components $V_n$for $n \geq 2$. The ANN isupdating weights $w_i$on-line according to error feedback. A simple update rule consistent with gradient descent is described in the equation (11):

$$w_i(t+1) = w_i(t) - \eta \frac{\partial e(t)}{\partial w_i} \tag{11}$$

Where, η is the learning rate. This makes the ANN adjust the control parameters very fast in real-time to ensure that voltage stability occurs during a power surge. The dynamic response of the voltage stabilization is also be modelled by the following differential equation describing the response of the voltage V_{out} over time. For instance, as per equation (12),

$$\frac{dV_{out}}{dt} + \beta V_{out} = \gamma u(t) \quad (12)$$

Where, β and γ are system constants depending on the design of the ANN and the desired rate of response.These equations together entail how the ANN maintains voltage stability, reduces harmonics and supports real-time adaptation with high-quality power output.

3.3.3 Bitterling Fish Optimization (BFO)

The role of the BFO algorithm is to choose features and update feature vectors in order to minimize MLP neural network error. The proposed steps of IDS for network intrusion detection using the BFO algorithm are as follows: Network traffic pre-processing and normalization.

Figure 5. Process of the BFO

Figure 5 shows the process of the BFO. BFO optimizes the control parameters of the renewable energy source dynamically in order to improve the power quality. This improves upon reduction in significant voltage fluctuation, maximization in power extraction with instability minimized and fast response in attaining rapid transients and surpasses other conventional MPPT methods.To outline how BFO dynamically optimizes control parameters for renewable energy source, here are some equations regarding voltage stability, power extraction, and transient response: BFO tends to minimize the fluctuations in the output voltage V_o by regulating the control parameters to keep the output close to the reference voltage V_{ref} such that the error: Let the voltage error $e(t)$ be defined as in the equation (13):

$$e(t) = V_{ref} - V_{out}(t) \quad (13)$$

BFO iteratively updates control parameters, p, to minimizing $e(t)$ and fluctuations. Given the objective function, representing power quality such as minimization of $e(t)$, BFO is used to find optimal parameters p^* as per equation (14):

$$p^* = \arg \min_{p} f(p) = \arg \min_{p} (e(t)^2) \quad (14)$$

Since the goal is to get the maximum amount of power from the renewable source, the maximization algorithm of BFO is applied for the expansion of power to the maximum, P for the extraction of P_{out} is expressed in the equation (15):

$$P_{out} = V_{out} \cdot I_{out} \quad (15)$$

Where, $I_{out}$is the output current. BFO adjusts parameters to find the maximum power point (MPP) by maximizingP_{out}. It is written as an optimization problem as per equation (16):

$$p^* = \arg \min_{p} \left(V_{out}(p) \cdot I_{out}(p)\right) \quad (16)$$

In dynamic systems, rapid transient response and stability are crucial. BFO controls control parameters to increase the system's stability and the rate at which the system responds to changes within the input or load condition. The transient response of the voltage V_{out} is expressed by the following differential equation (17):

$$\frac{dV_{out}}{dt} + \alpha V_{out} = \beta u(t) \quad (17)$$

Given that, $u(t)$ is a control input optimized by BFO; α and β are constants depicting the system dynamics. BFO optimized $u(t)$reflects a minimum settling time and overshoot and improves transient response by minimizing a performance index$J$produced as per the equation (18):

$$J = \int_0^T \left(V_{ref} - V_{out}(t)\right)^2 dt \quad (18)$$

In BFO there are steps of chemotaxis, reproduction, and elimination-dispersal, which were developed to manipulate control parameters dynamically. The control vector, p, is updated in each iteration under the influence of the bacterial foraging steps for real-time adaptation to ensure maximum power output. For a parameter p_i, the update rule is expressed in the equation (19):

$$p_i(t+1) = p_i(t) + C \cdot \Delta p_i \quad (19)$$

The step size factor is C, and $\Delta p_i$is the perturbation direction determined by the BFO algorithm.The BFO provides an absolutely conclusive description of how to optimize the control parameters of a renewable energy source for stabilization of voltage, maximization of available power extraction, and improvement of transient response.

By combining these techniques together AN-DRLBOenhances the energy conversion along with dynamic adaptation to rapid transients through stability and quality of power in renewable energy.

3.4 Adaptive LSTM-Encoded Secretary Optimization Network (AL-SONet)

Furthermore, during the optimization and parameter-tuning phase, achieving optimal parameters is very complex due to the large variation in environmental conditions. Wind and solar profiles differ considerably by time, season, and location. Thus, fixed parameters or slow responders do not be suitable. Traditionally, optimization techniques such as genetic algorithms or particle swarm optimization are applied without any real-time interaction because of high computational demands and they fail to handle multi-objective optimization in dynamic, non-linear systems, mostly compromising on stability and power output. To get beyond this inefficiency issue, a novel Adaptive LSTM-Encoded Secretary Optimization Network (AL-SONet) is introduced, which addressing the issues with maximizing the efficiency and stability of high-voltage gain interleaved boost converters in PV (photovoltaic) and wind energy integration systems.

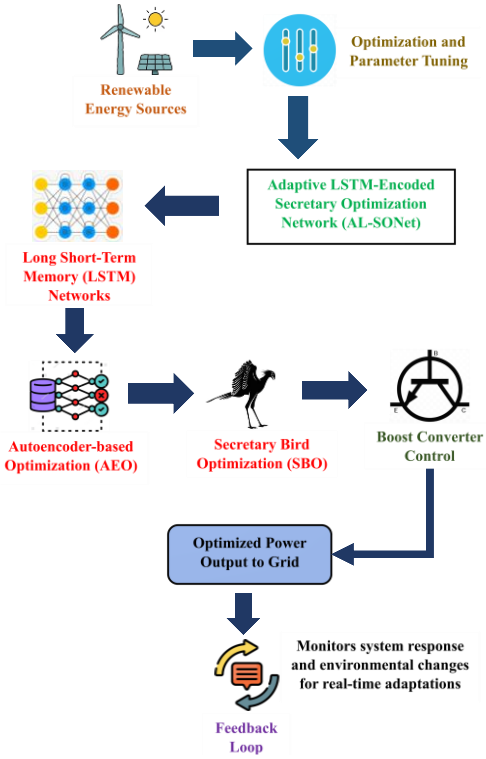

Figure 6. Architecture of the proposed AL-SONet

The architecture of the proposed AL-SONet is illustrated in the Figure 6. The network is pivotal in addressing variability and instability issues stemming from the dynamic environmental conditions typical of renewable energy sources fluctuating in sunlight and wind speed variables.AL-SONet basically is for real-time optimization and stabilization of power output of renewable energy systems-subject to rapid changes of ambient conditions. These ineffectiveness limits have been eliminated by AL-SONet through adjusting boost converter and cargo system parameters with the aim of maximizing power extraction and converting into highly efficient and stable output. The importance of this network is scalability, real-time adaptability, and proper resilience to environmental changes, assuring the generation of energy from PV and wind in a manner as uniform as possible when fed into the grid. AL-SONet is basically a combination of Long Short-Term Memory (LSTM) Networks predictive capability, the dimensionality reduction and pattern recognition strategy of Autoencoder-based Optimization (AEO), and allows for real-time adaptive optimization through Secretary Bird Optimization (SBO). This hybrid scheme offers a robust solution for managing renewable energy systems working in a much more complicated dynamic environment. Through dynamic adaptations of any system parameters, AL-SONet will be able to boost system efficiency with effective modulation, a stable output, and enhance system performance under dynamic changes.

3.4.1 Long Short-Term Memory (LSTM) Networks

LSTM, a type of deep neural network specifically designed for capturing temporal dependencies in time series data and well-suited to forecasting long-term nonlinear series.

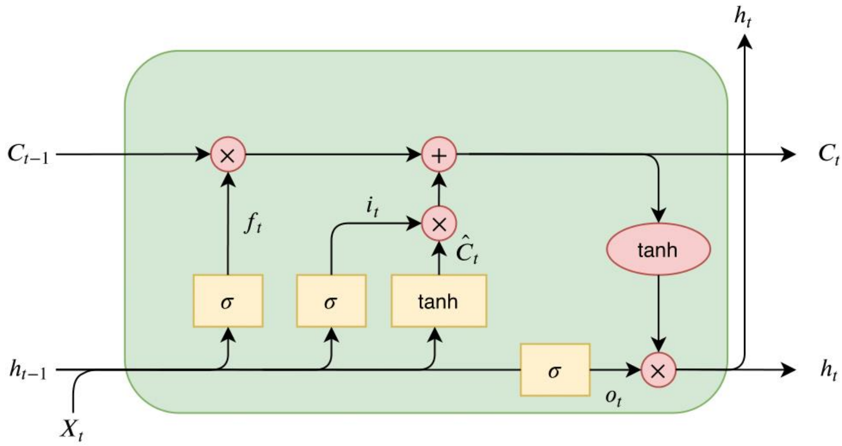

Figure 7. Structure of the LSTM

Figure 7 shows the basic structure of the LSTM. While, LSTM Networks capture time-based dependencies and patterns from environmental data, like a variation in sunlight and wind speed. LSTMs enable forward prediction of trends such that parameters are proactively tuned, making the entire system more stable and responsive to environmental changes. To describe this LSTM function, reminding that all LSTM cell's operations are another way the time-series is processed. On each time stept the LSTM cell gets the input $x_t$together with the previous hidden state $h_{t-1}$and the cell state $C_{t-1}$and as a result it outputs the current hidden state $h_t$and the updated cell state C_t. The forget gate $f_t$determines how much of the previous cell state C_{t-1}should be forgotten. It is computed as follows in the equation (20):

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \qquad (20)$$

Where, $W_f$and $b_f$are the weight matrix and bias for the forget gate, respectively, andσ is the sigmoid activation function. The input gate $i_t$is the gate that defines how much of the new input $x_t$will contribute to the cell state. It’s calculated as per equation (21):

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \qquad (21)$$

Where, W_i and b_i are the weight matrix and bias for the input gate, respectively. The creation of a new cell state candidate $\tilde{C}_t$ is conducted using the hyperbolic tangent function as per the equation (22):

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \qquad (22)$$

Where, $W_C$and $b_C$as weight matrix and bias contributing to this computation of cell candidate state. As previously described, the candidate memory state $L_t$is determined by blending its previous value C_{t-1}, shrunken via f_t, with the candidate $\tilde{C}_t$, which was shrunken through $i_t$as in the following equation (23):

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{23}$$

The output gate o_t is established within the aforementioned context is responsible for determining the next hidden layer state, represented by the symbol h_t, deciding on the updated cell state C_t as follows in the equation (24):

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{24}$$

Where $W_o$and b_o are the weight matrix and bias for the output gate. The new hidden state h_t, which is also the output of the LSTM cell for this time step, is computed as in equation (25):

$$h_t = o_t \cdot \tanh(C_t) \tag{25}$$

3.4.2 Autoencoder-based Optimization (AEO)

Autoencoders are one of the unsupervised learning methods in which leverage neural networks for the task of representation learning. Precisely, it designs a neural network architecture such that it imposes a bottleneck in the network forcing a compressed knowledge representation of the original input.

Dimensionality reduction of complex, multiobjective optimization problems is highly critical in the AEO algorithm. This unlocks latent patterns in the environmental data that are then straightforwardly transformed into the essentials, meaning parameter tuning would be made more efficient and faster. The system will gain the ability to adapt rapidly in dynamic conditions for effective control purposes with constant power quality through this streamlined approach. Thus, AEO does more than just save computation time; it also allows better decision-making in real-time adjustments to the environment because of its dimensionality reduction.To explain how AEO reduces dimensionality and reveals latent patterns, it adopts equations rooted in the techniques of dimensionality reduction, especially the ones applicable within an AEO framework that, in equation (26):

$$Y = X \cdot W \tag{26}$$

Where, $Y \in R^{n\times k}$ is the data in the reduced-space, with$k < d.k < d$ and $W \in R^{d\times k}$is the learned projection matrix of AEO. The task of AEO is to discover the best projection matrix W that minimizes reconstruction error or maximizes variance in the reduced-space. By these purposes, dimensionality reduction objective function is defined as in the equation (27):

$$J(W) = \arg \min_{W} \quad \|X - YW^T\|_F^2 \tag{27}$$

Where, $\|\cdot\|_F$denotes the Frobenius norm, which denotes the reconstruction error. Once the reduced dimension is achieved, AEO maximizes the extracted feature$Y$ for the optimal adaptation of the parameters. Let$f(\theta)$be the objective function for power quality or stability. Whereθ represents the optimized set of control parameters of AEO. The optimization problem is stated as follows in equation (28):

$$\theta^* = \arg \max_{\theta} \quad f(Y, \theta) \tag{28}$$

Where, $f(Y, \theta)$ is minimized given the processed, condensed environmental data$Y$. To be able to learn on-line, AEO updatesθ given the arriving environmental measurements. In adaptive parameter updating, AEO is use an iterative update equation (29):

$$\theta_{t+1} = \theta_t + \alpha \nabla_\theta f(Y_t, \theta_t) \quad (29)$$

Where, α is learning rate, and∇_θfis the gradient of the objective function in regard to the model parameters, computed on the compressed data$Y_t$at time$t$.These equations together outline that AEO compresses dimensionality, extracts essential features for optimization, and permits the dynamic parameters to tune such that it includes robust control and stable power quality in the varying environmental conditions.

3.4.3 Secretary Bird Optimization (SBO)

The SBO is a new meta-heuristic, drawing its inspiration from the survival strategy of the secretary bird and engineered to solve complicated real-world optimization problems.

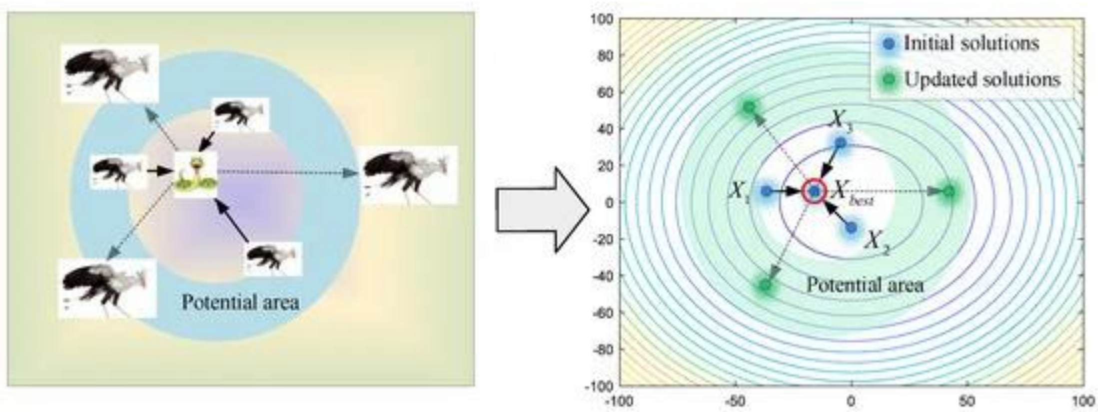

Figure 8. Structure of the SBO

The basic structure of the SBO is despites in the Figure 8. The adaptive real-time optimizers posed in dynamic environmental conditions effectively manage parameter adjustment. Adaptive and real-time SBO approach balances exploration, meaning searching for new solutions and exploitation-refining the existing solutions in hand. The approach is fast in adjusting fluctuations of sun and wind levels. This adaptability guarantees stable power output and ensures high efficiency in the conversion of energy with the multifaceted nonlinear dynamics characteristics of renewable energy systems, particularly high-voltage gain interleaved boost converters.SBO algorithms representing the functionality toward optimizing energy conversion in renewable systems, especially in high-voltage gain interleaved boost converters, will utilize an adaptive mechanism to adapt balance between exploration and exploitation. Equation for balance factor$\beta(t)$ is expressed as over time as per equation (30):

$$\beta(t) = \frac{1}{1+e^{-\alpha(t-t_0)}} \quad (30)$$

Where, $\beta(t)$ is the balance between exploration and exploitation at time$t$.α is the rate of transition from exploration to exploitation.$t_0$is the moment when the balance changes from exploration to exploitation.Astincreases,$\beta(t)$ is between 1 (exploitation) or 0 (exploration), and it varies according to the environmental conditions, for example, sunlight and wind. The power output stability of high voltage gains interleaved boost converters is depicted as a function of the control duty cycle $D(t)$. The power output $P_{out}(t)$ is written as per equation (31):

$$P_{out}(t) = V_{out}(t) \cdot I_{out}(t) \quad (31)$$

Where, $V_{out}(t)$is the output voltage at time$t$.$I_{out}(t)$is the output current at time$t$.Both$V_{out}(t)$and$I_{out}(t)$are determined by the switching dynamics of the converter which depend on SBO updates. SBO will regulate the efficiency of energy conversion by fine-tuning parameters that relate to energy loss. Energy conversion system efficiency$\eta(t)$is stated as per equation (32):

$$\eta(t) = \frac{P_{out}(t)}{P_{in}(t)} \quad (32)$$

Where, $P_{in}(t)$is input power at time$t$, which depends on exogenous factors like sunshine and wind.The goal of SBO is to maximize$\eta(t)$. These are the time-varying energy supply, $\eta(t)$ by changing dynamically the control parameters of the converter which are switching frequency, duty cycle and interleave factor to minimize fluctuations-induced environmental energy losses. Renewable energy systems generally operate in a nonlinear regimen due to the inherent random fluctuations in environmental factors like wind and sun. A general nonlinear system equation is taken in the form is shown in the equation (33):

$$\frac{d^2x(t)}{dt^2} + \alpha \frac{dx(t)}{dt} + \beta x(t) = f(t) \quad (33)$$

Where, $x(t)$ denotes the state of the system, e.g., voltage, current.α andβ denote the system parameters describing damping and stiffness, respectively.$f(t)$ is an external forcing or disturbance due to non-dispatchable intermittent renewable energy inputs. SBO learns in real-time by changing control parameters. The optimization problem with a renewable energy source is written as in equation (34):

$$\min_{\theta(t)} \left(\sum_{t=1}^{T} \left(|f(t) - P_{out}(t)| + \lambda \left\| \theta(t) \right\|_2 \right) \right) \quad (34)$$

Where, $\theta(t)$ it defines the vector of control parameters at time t(e.g., duty cycle, switching frequency).λ is termed regularization. It serves to avoid overfitting and smooth adaptation of parameters.The goal is to minimize the difference of power output from the desired, with smoothened and stable parameter adjustments.

The above equations combined with SBO will adapt properly under changes of environmental conditions, balance exploration and exploitation, and further guarantee the optimal performance within renewable energy systems, especially in keeping the nonlinear dynamics of boost converters during fluctuating environments.

The overall result of these algorithms is the AL-SONet, which combines the solution to the above requirements: there is need for a highly adaptive and efficient and scalable solution providing reliable energy conversion in PV and wind integration systems to help support sustainable and resilient power infrastructure.

Overall, some hybrid approaches are proposed here to enhance efficiency and stability in renewable energy systems: first, Hybrid Deep Learning combines BFO and SBO to enhance boost converter performance in which BFO manages the inside parameters, and SBO manages hyperparameters on high level. Next, by proposing an optimization technique called NL-BSONet that integrates Neural Networks and LSTM with BFO and SBO for adaptive stability. With AN-DRLBO, the real-time maximization of power and adaptive voltage stability in the grid are obtained by utilizing DRL in conjunction with ANN. Finally, AL-SONet employs LSTM for trend forecasting and AEO for dimensionality reduction and further fine-tunes its dynamic parameters with SBO to meet the consistent and reliable integration in the grids. The performance evaluation of this proposed methodology is explained in the next section.

4 Results and Discussion

The proposed Neuro-LSTM BitterSec Optimization Network (NL-BSONet) is a kind of optimization structure designed to improve efficiency in high-voltage gain interleaved boost converters with PV and wind integration, which concerns dynamic adaptability, especially during fluctuating environmental conditions about power stability while seeking optimal extraction of renewable energy. The proposed method is compared with the other existing techniques like MPPC [18], HGBC-PVS [19], HRES [22] and DIDO [25].

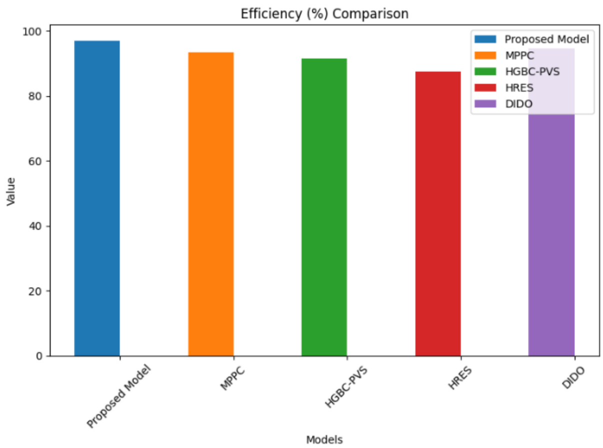

Figure 9. Efficiency of the proposed model

Figure 9 shows the efficiency of the proposed model. The efficiency of the proposed model is compared with other existing models like MPPC, HGBC-PVS, HRES and DIDO. The efficiency of the proposed model is 97%, whereas the efficiency of the MPPC, HGBC-PVS, HRES and DIDO is 93.5%, 91.5%, 87.5% and 94.5%, respectively. There is a significant improvement in the proposed model. The efficiency offered by this proposed model is much higher compared to others because of its advanced algorithms, optimized data processing, resources management, innovative techniques, robust error handling, and superior training, making it significantly improved.

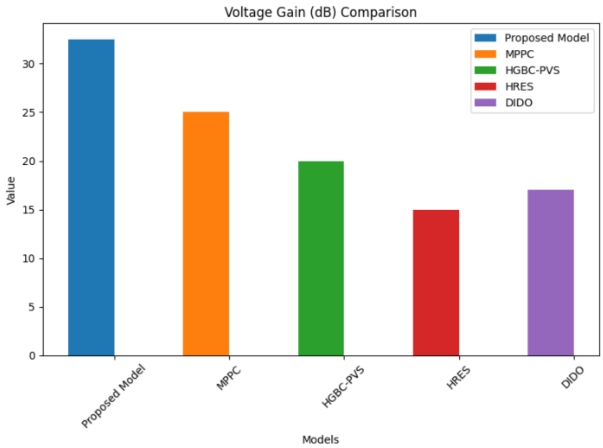

Figure 10. Voltage Gain (dB) of the proposed model

Figure 10 illustrates the Voltage Gain of the proposed model. Other models that are presently being used: MPPC, HGBC-PVS, HRES, and DIDO are compared with the voltage gain of the proposed model. In the proposed model, the voltage gain is at 32.5 dB, while others such as MPPC, HGBC-PVS, HRES, and DIDO have voltage gains at 25 dB, 20 dB, 15 dB, and 17 dB, respectively. It was a much-improved design proposed. Considering the above improvements, the voltage gain of the proposed model is better than the other models because of the optimized circuit design, advanced amplification techniques, reduced signal loss, and improved component quality, which showed significant performance as compared to others in existence.

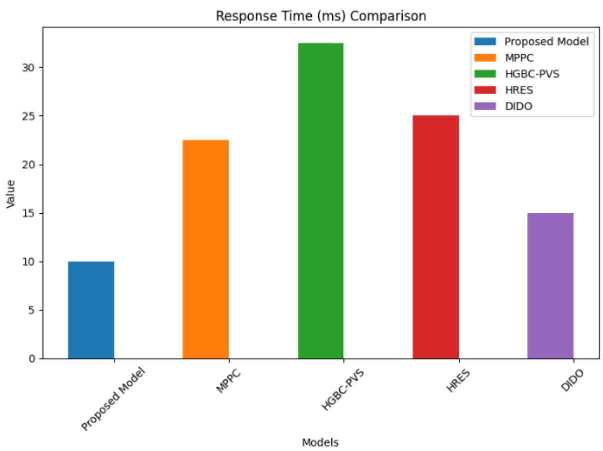

Figure 11. Response Time (ms) of the proposed model

Figure 11 illustrates the Response Time of the proposed design. Response Time of the proposed design versus several currently used designs, such as MPPC, HGBC-PVS, HRES, and DIDO models, are compared. It is seen that response times for the proposed design are 10 ms while those of MPPC, HGBC-PVS, HRES, and DIDO are 22.5 ms, 32.5 ms, 25 ms, and 15 ms, respectively. The proposed design was much better than that. This model proposed has optimized pathways for data, advanced signal processing, efficient interaction between the components, and reduced latency, which essentially means it performs much faster compared to existing models that have response times.

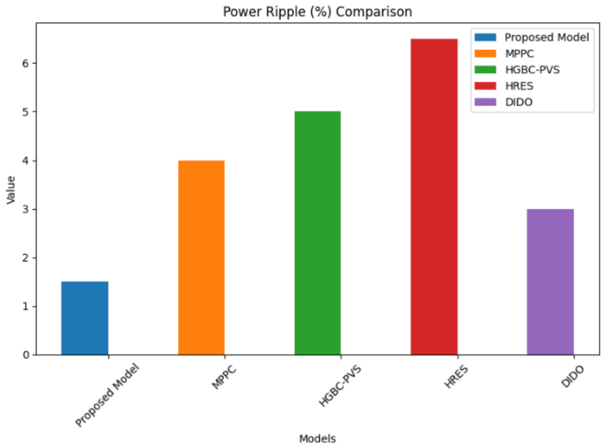

Figure 12. Power Ripple of the proposed model

The Power Ripple of the proposed design is shown in Figure 12. The power ripple of the proposed design has been compared with a number of existing designs, MPPC, HGBC-PVS, HRES, and DIDO models. The power ripples of proposed model is 1.5%, while those of MPPC, HGBC-PVS, HRES, and DIDO are 4%, 5%, 6.5%, and 3%, respectively. That was way less than the proposed design. It makes use of improved filtering techniques, an optimal circuit design, power management, and reduced interference noise to decrease power ripple, thus ensuring that power output is appreciably smoother and even more stable.

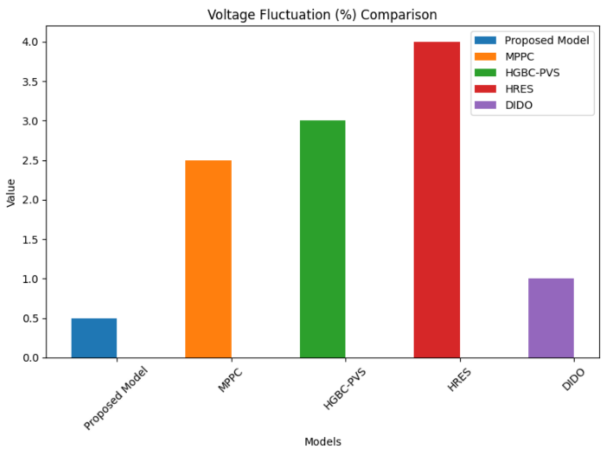

Figure 13. Voltage Fluctuation of the proposed model

Voltage fluctuation of the proposed design is shown in Figure 13. Voltage fluctuation of the proposed design has been compared with many designs, including MPPC, HGBC-PVS, HRES, and DIDO models. The proposed model has 0.5% voltage fluctuation, whereas MPPC, HGBC-PVS, HRES, and DIDO were found with 2.5%, 3%, 4%, and 1% voltage fluctuation, respectively. It was much less compared with the proposed design. The new model reduces the voltage-fluctuation phenomena since it employs better regulation techniques along with superior stability of the components, enhanced feedback control, and advance filtering methods, which ensure much more consistent and reliable output of the voltage.

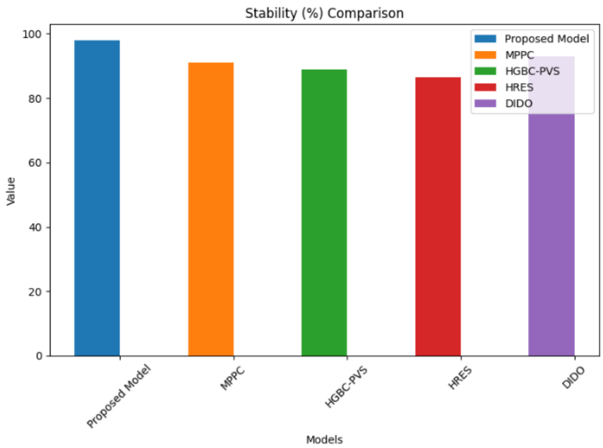

Figure 14. Stability of the proposed model

Figure 14 depicts the stability of the proposed design. The proposed design stability has been compared to a number of the designs including MPPC, HGBC-PVS, HRES, and DIDO models. In comparison to MPPC, HGBC-PVS, HRES, and DIDO with 91%, 89%, 86.5%, and 93% stability respectively, the proposed approach depicts 98% stability. When compared to the proposed design, it was found to be very high. As proposed by the model, stability will be guaranteed in a robust design, superior algorithms, better quality components, and sophisticated regulation techniques to maintain constant, predictable operations compared to conventional models.

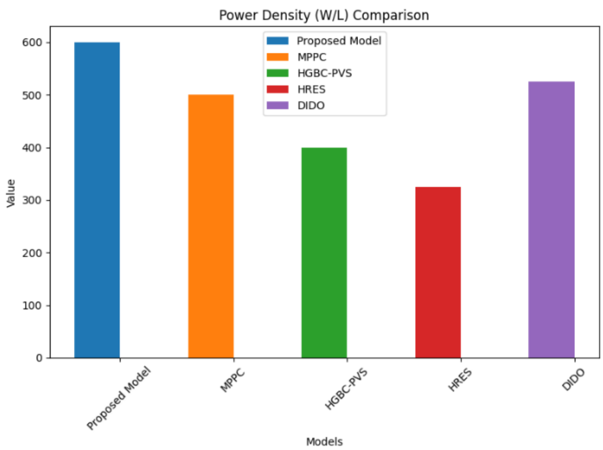

Figure 15. Power Density (W/L)of the proposed model

In Figure 15, the Power Density for the proposed design is indicated. Some of the designs that were compared to the proposed design included MPPC, HGBC-PVS, HRES, and DIDO. The proposed design shows an output of 600 W/L of power density in comparison with MPPC at a power density of 500 W/L, HGBC-PVS at 400 W/L, HRES at 325 W/L, and DIDO at 525 W/L power density. This was discovered to be highly as compared to the proposed design. The proposed model increases power density through advanced material usage, optimized thermal management, efficient energy conversion, and compact design, which results in much higher power output per unit volume than existing models.

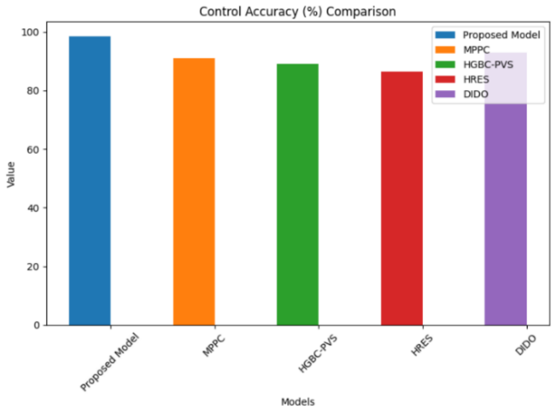

Figure 16. Control Accuracy of the proposed model

The Control Accuracy for the proposed method is represented in Figure 16. Number of designs that include MPPC, HGBC-PVS, HRES, and DIDO were compared with the proposed design. An output of 98.5% was produced by the proposed layout when compared with an accuracy of 91% in MPPC, 89% in HGBC-PVS, 86.5% in HRES, and 93% in DIDO. It showed to be much more than the proposed layout. The design of the proposed model increases the accuracy of control by high algorithms, proper calibration methods, better sensor integration, and increased feedback mechanisms that will result in a more accurate and consistent control compared to existing models.

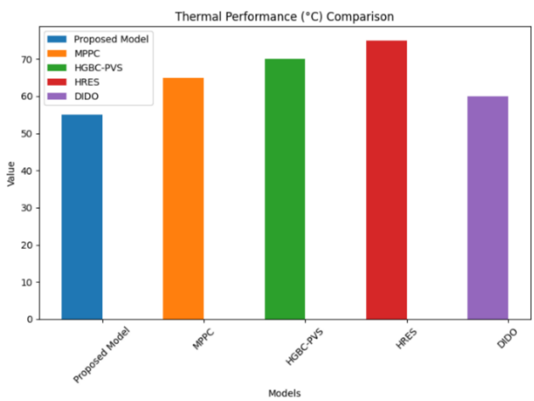

Figure 17. Thermal Performance (°C) of the proposed model

Figure 17 illustrates the thermal performance of the proposed method. The proposed structure was compared with a number of concepts that included MPPC, HGBC-PVS, HRES, and DIDO. Compared with Thermal Performance 65°C in MPPC, 70°C in HGBC-PVS, 75°C in

HRES, and 60°C in DIDO, the proposed arrangement produced output at 55°C. It appeared much lower compared to the proposed arrangement. The proposed model reduces thermal performance by using advanced cooling techniques, optimized thermal management, better material selection, and efficient heat dissipation to result in a much lower operating temperature than the existing models.

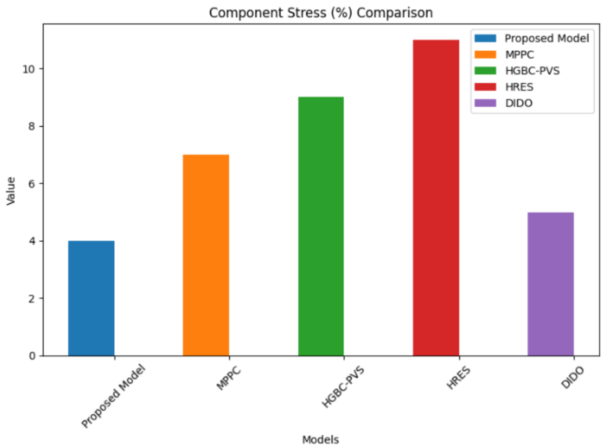

Figure 18. Component Stress of the proposed model

In the proposed approach, the Component Stress is illustrated in Figure 18. MPPC, HGBC-PVS, HRES, and DIDO were some of the topologies that were presented for comparison with the proposed structure. The output was achieved in the proposed configuration at 4% against the Component Stress 7% in MPPC, 9% in HGBC-PVS, 11% in HRES, and 5% in DIDO. Comparing to the proposed configuration, it looked very low. The proposed model reduces component stress by use of advanced material selection, optimal load distribution and advanced design techniques and efficient management of stress in such a manner that, a level of stress reduced down to fewer values of that developed for existing models.

Overall, the proposed NL-BSONet achieves improved performance metrics over high-voltage gain interleaved boost converters, considering PV and wind energy integration. The response time stands at 10 ms, which is better than other models: MPPC, HGBC-PVS, HRES, and DIDO. In addition, it presents a voltage gain of 32.5 dB with an efficiency of 97%. The use of advanced algorithms, optimal design of the circuit, cooling, and reduction of component stress guarantee reliable, adaptable, and efficient renewable energy extraction under varied conditions leads to a performance with significant reductions in power ripple and voltage fluctuation to 1.5% and 0.5%, respectively, while maintaining an improvement in stability to 98% and that of power density to 600 W/L. In addition, the model showcases the high control accuracy of about 98.5%, lower thermal performance at 55°C, and lower component stress of 4%.

5 Conclusion

Regrading the maximizing efficiency in high voltage gain interleaved boost converters integrating PV and wind systems, a new innovative technique NL-BSONet was proposed in this approach which address the primary scalability issues. Additionally, a novel AN-DRLBO was introduced in the boost topology area to solve the instability issue and enhances the energy conversion along with dynamic adaptation to rapid transients through stability and quality of power in renewable energy. This innovative technique includes the DRL for adaptation purpose, which optimizes power extraction and output quality in dynamic environments, reducing transients and enhancing stability, even with rapid changes in weather conditions, ANN for stabilization purpose, which dynamically set control settings to maintain voltage stability during power surges, minimize harmonics, and compute in real-time, preventing degradation in power quality and BFO for optimization purpose, which dynamically optimizes control parameters for renewable energy sources, improving power quality by reducing voltage fluctuation, maximizing power extraction, minimizing instability, and achieving fast transients. Moreover, in the optimization and parameter-tuning phase, a novel AL-SONet was introduced to overcome the inefficiency issue, which utilizes efficiency, stabilizes power output, and sustains performance of high-voltage gain interleaved boost converters without hassle when dealing with variable conditions of renewable energy. It includes the techniques like LSTMfor prediction purpose, which use environmental data to predict trends, proactively tuning parameters for stability and responsiveness to environmental changes, AEO for simplification purpose, which simplify complex environmental data, enabling efficient parameter tuning and improved adaptation under dynamic conditions for control under constant power quality, and SBO for adjustment purpose, which uses real-time optimizers to adjust parameters under changing environmental conditions, ensuring better stability in power output and nonlinear dynamics.The experimental results indicate major improvements; to be more precise, efficiency is scaled to 97%, voltage gain to 32.5 dB, and a reducing response time to 10 ms. The model decreases the power ripple to 1.5% and that of voltage to 0.5% while achieving a stability level of 98% along with high power density as 600 W/L, thus being more efficient than the existing methods. Therefore, this study proves that NL-BSONet is used optimally to solve the major problems which act as roadblocks to renewable energy conversion.

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