EPCMSDB: Design of an ensemble predictive control model for solar PV MPPT deployments via dual bioinspired optimizations

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Abstract. With the increasing demand for renewable energy, solar power has emerged as a promising option for sustainable power generation. However, the effectiveness and efficiency of solar power systems rely on the ability to effectively manage their performance, making it essential to develop efficient control models. This paper proposes a novel ensemble predictive control model for solar deployments using bio-inspired optimizations to improve load-connected solar deployments’ performance. The proposed model integrates multiple control devices, including Maximum Power Point Tracker, Proportional-Integral-Derivative, Proportional-Integral, and Fuzzy Logic Controllers, to selectively control the solar Photovoltaic systems. The proposed model incorporates a predictive control operation utilizing an LSTM-GRU (Long Short-Term Memory-Gated Recurrent Unit) with the VARMA (Vector Auto-Regressive Moving Average) model, which can accurately predict the future power generation of the solar system. This feature can facilitate efficient energy management and increase the system’s performance for different use cases. Implement a SEPIC (Single Ended Primary Inductor Capacitor) converter design to improve the system’s overall efficiency levels. To validate the effectiveness of the proposed approach, the author conducted experiments using real-world data and compared the proposed results with other control strategies. The results demonstrate that the ensemble predictive control model based on bio-inspired optimizations outperforms the existing control models regarding accuracy, efficiency, and stability levels. The proposed model has the potential to significantly improve the performance of load-connected solar deployments, offering a more practical approach to solar power generation. The combination of predictive control operations with bio-inspired optimizations can facilitate the design of sustainable energy systems with higher efficiency and accuracy.

Keywords: Solar Power, MPPT, PI, PID, Fuzzy, VARMA, LSTM, GRU.

Abbreviations

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<tr>
<td>MPPT</td>
<td>Maximum Power Point Tracker</td>
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<td>PID</td>
<td>Proportional-Integral-Derivative</td>
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<td>PI</td>
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<td>FLC</td>
<td>Fuzzy Logic controllers</td>
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<td>PV</td>
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<td>LSTM</td>
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<td>GRU</td>
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<td>SEPIC</td>
<td>Single Ended Primary Inductor Capacitor</td>
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<td>VARMA</td>
<td>Vector Auto-Regressive Moving Average</td>
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<td>GWO</td>
<td>Grey Wolf Optimizer</td>
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<td>EER</td>
<td>Energy Efficiency Ratio</td>
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<td>CSP</td>
<td>Cost Savings Percentage</td>
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<td>CSSI</td>
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<td>WPI</td>
<td>Weighted Performance Index</td>
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<td>Settling Time</td>
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1 Introduction

In recent years, solar power has emerged as a promising option for sustainable power generation due to its environmental benefits and cost-effectiveness. The growing demand for renewable energy sources has led to an increase in the deployment of solar power systems, especially in load-connected applications [1]. However, the effectiveness and efficiency of solar power systems rely on effectively managing their performance [2], which makes it essential to
develop efficient control models [3]. The author proposes a novel ensemble predictive control model for solar deployments using dual bio-inspired optimizations. Proposed model integrates multiple control devices, including Maximum Power Point Tracking (MPPT), Proportional-Integral-Derivative (PID), Proportional-Integral (PI), and Fuzzy Logic Controllers (FLC) [4], which are selectively controlled by a bio-inspired optimization technique to determine the optimal parameters and configurations [5]. Furthermore, Model incorporates a predictive control operation using a VARMA-GRU (Vector Auto-regressive Moving Average-Gated Recurrent Unit) with an LSTM (Long Short-Term Memory) model to accurately predict future power generation, which can facilitate more efficient energy management capabilities [6].

The proposed model offers a more comprehensive and efficient approach to control, significantly improving the performance of load-connected solar deployments. The author conducts experiments using real-world data to demonstrate the effectiveness of the proposed model compared to existing control strategies.

The remainder of this paper is organized as follows:

- **Section 2** provides an overview of the related work in the area of solar power control models.
- **Section 3** presents the proposed ensemble predictive control model, including the dual bio-inspired optimization technique, control devices, and predictive control operation.
- **Section 4** details the result in analysis and comparison.
- Finally, conclude the paper in **Section 5** with a summary of our findings and future work recommendations.

# 2 Review of existing control model

The optimization of solar power systems has been an active area of research in recent years due to the increasing demand for renewable energy sources [7]. Various control strategies have been proposed to improve the performance and efficiency of load-connected solar deployments [8, 9]. In this section, the author reviews some related work in solar power control models [10–12].

- Fuzzy Logic Controllers (FLC) [22] have also been proposed for solar power systems [23, 24]. Fuzzy controllers use linguistic variables and rules to control the system, making them more robust to disturbances and noise than PID controllers. Fuzzy controllers [25] have been shown to improve the efficiency and performance of solar power systems [26].
- Predictive control is another approach that has gained attention in recent years for different use cases [27, 28]. Predictive control methods use a model of the system to predict future behavior and optimize the control input accordingly for different scenarios [29]. The predictive control approach [30], has been shown to improve the performance of solar power systems, especially in situations with varying weather conditions [31, 32].
- Bio-inspired optimization techniques have also been proposed for solar power systems [33]. These methods use algorithms to maximize available power from the solar panels by varying the duty cycle of the converters [14]. Various MPPT algorithms have been proposed, including Perturb.
- MPPT is one of the most widely used control techniques for solar power systems [13]. MPPT methods aim to extract the maximum available power from the solar panels by varying the duty cycle of the converters.
- PID controllers are another commonly used control technique for solar power systems Incremental Conductance (INC) [16], and Fractional Open Circuit Voltage (FOCV) [18]. PID controllers aim to maintain the output voltage or current at a desired value by adjusting the converter’s duty cycle based on the error between the desired and measured values and samples [19]. However, PID controllers are susceptible to noise and disturbances [20], which can affect their performance levels [21].ired by natural processes, such as genetic algorithms, particle swarm optimization, and ant colony optimization, to optimize the control Perturb and Observe (P&O) [15, 17], among others parameters of the systems [34, 35]. bio-inspired optimization techniques have been shown to improve the performance [36] and efficiency of solar power systems [37, 38].

This proposes a novel ensemble predictive control model for solar deployments [39, 40] using dual bio-inspired optimizations [41]. Our proposed model integrates multiple control devices, including MPPT, PID, PI, and Fuzzy controllers [42], which are selectively controlled [43] by a bio-inspired optimization technique to determine the optimal parameters and configurations [44]. Our model incorporates a predictive control operation using a VARMA-GRU with an LSTM model to predict future power generation accurately. The proposed model offers a more comprehensive and efficient control approach [45], significantly improving the performance of load-connected solar deployments [46].

# 3 Proposed design of an ensemble predictive control model for solar deployments via dual bio-inspired optimizations

As per the review of existing models for predictive control model for solar deployments, it can be observed that existing models are either highly complex or have lower efficiency for real-time scenarios. To overcome these issues, this text proposes designing an efficient novel ensemble predictive control model for solar deployments using dual bio-inspired optimizations, aiming to improve load-connected solar deployments’ performance. The author proposes a novel ensemble predictive control model for solar deployments using dual bio-inspired optimizations in this section. As per the flow of the model in Figure 1, it can be observed
that the proposed model integrates multiple control devices, including [47],

- MPPT,
- PID,
- PI,
- FLC.

To selectively control the solar PV systems [48, 49]. The suggested bio-inspired optimization strategy establishes each control device’s ideal parameters and configurations, making device control more comprehensive and efficient for varied scenarios. Moreover, the proposed model incorporates a predictive control operation utilizing a VARMA-GRU with LSTM method, which can accurately predict the future power generation of the connected solar PV systems. This feature can facilitate efficient energy management and increase the system’s performance for different use cases. Additionally, the researcher implements a SEPIC (Single Ended Primary Inductor Capacitor) converter design to improve the system’s overall efficiency levels. This section is segregated into different sub-sections to elaborate on the proposed design. Each sub-section describes a different component of the design process.

3.1 Conversion of collected samples into multi-modal feature sets

The proposed model uses a fusion of LSTM and GRU for converting the collected configurations of power, load, and controller parameters into multi-modal feature sets. Variables of LSTM are:

- Cell State \((C_t)\)
  It is a memory of LSTM.
- Hidden State \((h_t)\)
  It is an output of LSTM. It is a combination of Current input \((X_t)\) and cell state \((C_t)\)
- Tanh Function \((\tanh)\)
  It is used to regulate/Squish the values between \(1\) and \(-1\).
- Sigmoid Function \((\delta)\)
  It is used to regulate/Squish the value between \(0\) and \(1\). Sigmoid is used to Update or forget data. If the value is zero then it is used for the forgotten value. (It considers it as not important data). If the value is 1 then it is used for Kept as it is value (It considers it as important data). Values come out from Sigmoid between \(0\) and \(1\). The closer to \(0\) means to Forget. The closer to \(1\) means Kept.

There are three different gates that regulate the information flow in LSTM.

- Forget Gate \((f_t)\): This gate decides what information should be thrown away or kept. The forget gate is a combination of the previous hidden state \((h_t - 1)\) and current input \((X_t)\).
- Input Gate \((i_t)\): This gate decides what information should be updated or not updated. The input gate is a combination of the hidden state \((h_t - 1)\) and current input \((X_t)\). The input gate is multiplication with the candidate cell \((C_t)\).
- Output Gate \((o_t)\): This gate decides what the next hidden state should be. The output gate is a combination of the previous hidden state \((h_t - 1)\) and current input \((X_t)\). The input gate is multiplication with \(\tanh C\).

Fig. 1. Design of the proposed model for optimization of Solar PV Deployments.
Similarly, GRU also has various components such as: especially GRU has two extra gates:

- **Reset gate** \( (r_t) \): The reset gate is used to decide how much past information to forget.
- **Update Gate** \( (U_t) \): The update gate is used to decide what information to add or throw/remove.

The process of this conversion is iterative and can be observed in Figure 2.

To perform this conversion, all the collected feature sets are initially represented by an input feature vector \( i \), which is estimated via equation (1):

\[
   x_i = \text{var}(z^{(in)} \times U^t + h(t-1) \times W^t)
\]

where \( z^{(in)} \) is a collection of input feature samples, \( U \) and \( W \) represent constants of the LSTM process, while \( h \) represents the kernel matrix, which must be tuned for maximization of variance levels. These levels are estimated via equation (2):

\[
   \text{var}(x) = \frac{\left( \sum_{i=1}^{N} (x(i) - \sum_{j}^{N} x(j)/N)^2 \right)}{N+1}
\]

where \( N \) is the total count of input samples. Similar to the input vector, a set of three different vectors, namely functional \( (f) \), output \( (o) \), and convolutional \( (c) \) features, are also estimated via equations (3)–(5) as follows:

\[
   f = \text{var}(x^{(in)} \times U^f + h(t-1) \times W^f), \quad (3)
\]

\[
   o = \text{var}(x^{(in)} \times U^o + h(t-1) \times W^o), \quad (4)
\]

\[
   c = \tan h(x^{(in)} \times U^c + h(t-1) \times W^c). \quad (5)
\]

All these operators are fused to estimate an augmented temporal feature vector via equation (6),

\[
   T(out) = \text{var}(f(t) \times x^{(in)}_t + i \times c). \quad (6)
\]

Based on these feature sets, the kernel matrix is updated via equation (7),

\[
   h(out) = \tan h(T(out) \times h). \quad (7)
\]

These features are further processed via equations (8) and (9), where an augmented set of forgetting \( (z) \) and retaining \( (r) \) features are estimated as follows,

\[
   z = \text{var}(W(z) \times [h(out) \times T(out)]) \quad (8)
\]

\[
   r = \text{var}(W(r) \times [h(out) \times T(out)]). \quad (9)
\]

These vectors are fused via equations (10) and (11) to identify output feature vector sets.

\[
   x_{out} = (1 - z) \times h(t) + z \times h(out) \quad (10)
\]

\[
   h(t) = \tan h(W \times [r \times h(out) \times T(out)]). \quad (11)
\]

The value of \( h(t) \) is used to iteratively calculate LSTM features, which are used to calculate GRU features. This process is repeated till the convergence criteria of equation (12) are satisfied,

\[
   x_{out}^{(new)} \approx x_{out}^{(old)}. \quad (12)
\]

After condition (12) is satisfied, the process converges, and selected features are used to predict PV outputs. An error of less than 1% is ideally used for matching these value sets. These outputs are predicted by a VARMA Model, which is discussed in the next section of this text.
3.2 Design of the VARMA model for prediction of PV outputs

VARMA (Vector Auto-regressive Moving Average) models are commonly used in time-series analysis and forecasting, including for predicting Photovoltaic (PV) outputs. To perform this task, the proposed model uses a fusion of VARMA \((p, q)\) with VARMAX \((p, q)\) models. The VARMA \((p, q)\) model is represented via equation (13),

\[
X(t) = A(1)X(t-1) + A(2)X(t-2) + \ldots + A(p)X(t-p) + B(1)E(t-1) + B(2)E(t-2) + \ldots + B(q)E(t-q) + E(t)
\]

where \(X(t)\) is a vector of \(p\) time-series variables, in this case, the temporal LSTM and GRU PV outputs and features. \(A(1), A(2), \ldots, A(p)\) are \(p \times p\) matrices of coefficients that measure the impact of \(X(t-i)\) on \(X(t)\), where \(i = 1, 2, \ldots, p\), while \(B(1), B(2), \ldots, B(q)\) are \(p \times p\) matrices of coefficients that measure the impact of the past forecast errors \((E(t-1), E(t-2), \ldots, E(t-q))\) on \(X(t)\). \(E(t)\) is a vector of white noise error terms, assumed to be normally distributed with mean zero and constant variance levels. Similarly, the VARMAX \((p, q)\) model is represented via equation (14),

\[
X(t) = \begin{bmatrix}
A(1)X(t-1) + \\
A(2)X(t-2) + \\
\vdots + A(p)X(t-p) \\
\end{bmatrix} + \begin{bmatrix}
B(1)E(t-1) + \\
B(2)E(t-2) + \\
\vdots + B(q)E(t-q) \\
\end{bmatrix} + C(z) + E(t)
\]

where \(C\) is a vector of constants that capture the long-term trend or other factors that affect the PV outputs, and \(z\) is a vector of exogenous variables (such as weather data or other factors that may affect PV outputs) that are included in the model via LSTM and GRU feature sets. Based on output value \(X(t)\), the MPTT, PID, PI, and Fuzzy controllers are deployed, \(f(X, GWO)\) and \(f(E, GWO)\) represent the tuning factors for \(X\) and \(E\) variables, which are extracted via GWO operations. To perform these control tasks, an augmented set of controllers is needed, each of which is discussed in the following sub-section of this text.

3.3 Design of different controllers

- MPPT is a technique used to optimize the power output of PV systems by finding and maintaining the maximum power point (MPP) of the PV array. Different control algorithms can be used for MPPT, but one common approach is using a Perturb and Observe (P&O) algorithm, which works as per the following operations.
  1. Calculate the PV power via equation (15),

\[
P_{pv} = V_{pv} \times I_{pv}
\]

where,

- \(P_{pv}\) is the power generated by the PV array,
- \(V_{pv}\) is the PV voltage, and \(I_{pv}\) represents the PV current levels.
  2. Perturb the PV voltage via equation (16),

\[
V_{pv, new} = V_{pv, old} + \Delta V \times f(V, GWO)
\]

where,

- \(V_{pv, new}\) is the new PV voltage,
- \(V_{pv, old}\) is the previous PV voltage,
- \(\Delta V\) is a small increment in the PV voltage,
- \(f(V, GWO)\) represents the voltage tuning factor which is decided by the GWO process.
  3. Measure the new PV power via equation (17),

\[
P_{pv, new} = V_{pv, new} \times I_{pv, new}
\]

where,

- \(I_{pv, new}\) are the new PV current levels.
  4. Calculate the power change via equation (18),

\[
\Delta P = P_{pv, new} - P_{pv, old}
\]

where,

- \(P_{pv, old}\) represents the previous PV power levels.
  5. Determine the scope of the power change as follows.

- If \(\Delta P > 0\), the perturbation was in the proper scope (toward the MPP), and the voltage should be increased further, while if \(\Delta P < 0\), the perturbation was in the wrong scope (away from the MPP), and the voltage should be decreased for different input types.
  6. Adjust the PV voltage via equation (19),

\[
V_{pv, new} = V_{pv, old} + \Delta V \times sgn(\Delta P)
\]

where, \(sgn()\) is the sign function, which returns \(-1\) for negative values and \(+1\) for positive values under real-time scenarios, while \(f(pv, GWO)\) is the optimization constant for \(pv\) which is tuned via GWO operations.

7. Repeat steps 2–6 until the MPP is reached for different input types.

The above equations can be implemented in a microcontroller or a dedicated MPPT controller to continuously track the MPP of the PV array and maximize the power outputs.

- Similarly, PID control is a commonly used feedback control strategy in many industrial applications, including PV systems. The following operations do this,
Figure 3 work flow can be implemented in a microcontroller or a dedicated PID controller to regulate the PV voltage and maintain it at the desired set points. $K_p$, $K_i$, and $K_d$ gains can be tuned based on the system dynamics and the desired performance levels.

- PI control is a feedback control strategy commonly used in PV systems to regulate the PV voltage and maintain it at an augmented set of desired set points. This works as per the following operations,

Figure 4 processes were implemented on a micro-controller to regulate and maintain the PV voltage at the desired set points. The gains $K_p$ and $K_i$ were tuned based on the GWO Operations based on the system dynamics and the desired performance levels. PI control is more superficial than PID control, but it may not provide enough damping for systems with high dynamics or disturbances.

- Similarly, Fuzzy control, a type of feedback control strategy that uses fuzzy logic to regulate the PV voltage in photovoltaic PV systems, is also used to perform control operations. This process works via the following operations,

1. Define the input variables sets,
   - PV voltage error $(e)$.
   - Change in PV voltage error $(\frac{de}{dt})$.

2. Define the output variable for control operations,
   - A control signal $(u)$.

3. Define the fuzzy sets for the input variables under real-time scenarios,
   - **PV voltage error**: Negative Large (NL), Negative Medium (NM), Negative Small (NS), Zero (Z), Positive Small (PS), Positive Medium (PM), Positive Large (PL).
   - **Change in PV voltage error**: Negative (N), Zero (Z), Positive (P).

4. Define the fuzzy sets for the output variables under different conditions,
   - Control signal: Negative Large (NL), Negative Medium (NM), Negative Small (NS), Zero (Z), Positive Small (PS), Positive Medium (PM), Positive Large (PL).

5. Define the fuzzy rules as follows,
   - If $e$ is NL and $\frac{de}{dt}$ is N, then $u$ is PL.
6. Apply the fuzzy inference method to determine the control signals.

- Determine the degree of membership of the input variables in their respective fuzzy sets using the membership functions.
- Apply the fuzzy rules to determine the degree of membership of the output variable in its fuzzy sets using the minimum operator for the AND operation and the maximum operator for the OR operation.

7. Apply the control signal via equation (20),

$$ (pv) = I(pv, \text{nominal}) + u $$

where,

- $I(pv)$ is the PV current,
- $I(pv, \text{nominal})$ is the nominal PV current,
- $u$ is the set of control signals.

Thus, MPPT, PID, PI, and fuzzy PV control can be expressed by defining the input and output variables, fuzzy sets, fuzzy rules, fuzzy inference methods, and control signal operations. The control signal is obtained by applying the fuzzy logic to the input variables and the fuzzy rules and then defuzzifying the output variable sets. The control signal is then added to the nominal PV current to generate the actual PV current levels. The internal constants of these controllers are tuned by a GWO-based optimization process, which is discussed in the next section of this article.

3.4 Design of the GWO model for optimizing these controllers

Once the LSTM, GRU, and VARMA Models have selected the control operations, an efficient GWO-based optimization model is used to identify optimal tuning constants. These constants are estimated via the following process.

- Initially, an augmented set of NW Wolves is generated, each of which contains stochastic values of control constants. These control constants are estimated via equations (21)–(25) as follows,

$$ f(X, \text{GWO}) = \text{STOCH}(\text{Min}(X), \text{Max}(X)) $$
$$ f(E, \text{GWO}) = \text{STOCH}(0, 1) $$
$$ f(V, \text{GWO}) = \text{STOCH}\left(\frac{\text{Min}(V)}{\text{Max}(V)}, \text{Min}(V)\right) $$
$$ f(pv, \text{GWO}) = \text{STOCH}(0, 1) $$
$$ f(P, \text{GWO}) = \text{STOCH}\left(\frac{\text{Min}(P)}{\text{Max}(P)}, 1\right) $$

where,

- $\text{Min}(X)$ and $\text{Max}(X)$ represents minimum and maximum values for $X$.
- $\text{Min}(V)$ and $\text{Max}(V)$ represents minimum and maximum output voltage levels.
- $\text{Min}(P)$ and $\text{Max}(P)$ represents minimum and maximum power values for individually connected loads.
- STOCH represents a stochastic process.
Using these values, the VARMA, GRU, and LSTM processes are executed, along with the control operations, and a SEPIC Converter is used for simulations. Converter design can be observed in Figure 5, where different circuit components are displayed along with respective load sets. Based on the execution, Wolf fitness is estimated via equation (26),

\[
    f = \frac{EER \times CSP \times WPI \times RI}{CSSI \times Ts} \tag{26}
\]

where,

- EER represents the Energy Efficiency Ratio and is estimated via equation (27),
- CSP represents the Cost Savings Percentage and is estimated via equation (28),
- CSSI represents the Control Signal Smoothness Index and is represented via equation (29),
- WPI represents the Weighted Performance Index and is estimated via equation (30),
- TS represents the Settling Time, and is the time taken for the system output to settle within a specified range around the desired set-points,
- RI represents the Robustness Index and is estimated via equation (31) as follows,

\[
    CSSI = \frac{1}{\sum|du(t)|^2} \tag{29}
\]

where, \(du(t)\) is the change in control action at timestamp \(t\) for different input scenarios.

\[
    PI = w_1 \times EER + w_2 \times CSP + w_3 \times CSSI \tag{30}
\]

where \(w_1, w_2,\) and \(w_3\) are weights assigned to each performance parameter for different input conditions.

\[
    RI = 1 - \left(\frac{\sum|du(t)|}{T}\right) \tag{31}
\]

where \(T\) is the total simulation time for different simulation use cases.

- This fitness is estimated for each of the Wolves, and based on these fitness levels, a fitness threshold is estimated via equation (32),

\[
    f_{th} = \frac{1}{NW} \sum_{i=1}^{NW} f(i) \times LW(i) \tag{32}
\]

where LW is the Learning Rate for different Wolves and is tuned as per their types.

- Based on this threshold, Wolves are Marked as per the following conditions,

- If \(fw > 2 \times f_{th}\), then Wolf is marked as “Alpha” and is used to train “Beta” Wolf Sets.
- If \(fw > f_{th}\), then Wolf is marked as “Beta” and is used to train “Gamma” Wolf Sets. The learning rate of these Wolves is tuned via equation (33),

\[
    \text{Fig. 5. The SEPIC converter used for simulation operations.}
\]
employed and combined:

\[ \text{LW(Beta)} = \text{LW(Beta)} + \frac{\text{LW(Alpha)}}{\sum_{i=1}^{NW} \text{LW(i)}}. \]  

- If \( F_w > L \times F_h \), then Wolf is marked as “Gamma” and is used to train “Delta” Wolf Sets. The learning rate of these Wolves is tuned via equation (34),

\[ \text{LW(Gamma)} = \text{LW(Gamma)} + \frac{\text{LW(Beta)}}{\sum_{i=1}^{NW} \text{LW(i)}}. \]  

- Other Wolves are Marked as “Delta”, and their learning rate is modified via equation (35),

\[ \text{LW(Delta)} = \text{LW(Delta)} + \frac{\text{LW(Gamma)}}{\sum_{i=1}^{NW} \text{LW(i)}}. \]  

- This process is repeated for \( NI \) iterations, and different Wolf configurations are generated in each set of Iterations.

Due to these optimizations, the model can improve Energy Efficiency Ratio, Cost Savings Percentage, Control Signal Smoothness Index, Weighted Performance Index, TS, and Robustness Index for different scenarios. These parameters are evaluated for different circuit conditions and compared with existing models in the next section of this text.

3.5 Discussion about fusion of the proposed models

Multiple control techniques, including PI, PID, and FLC, are utilized and integrated into the ensemble predictive control model proposed for solar PV MPPT deployments. Here is a detailed explanation of how these control strategies are employed and combined:

- Combining the Control Techniques: The proposed ensemble predictive control model incorporates and combines the PI, PID, and FLC to reap the benefits of these control techniques. Each controller has a distinct function within the overall control strategy, allowing the system to adapt to various operating conditions and enhance performance. The control methods were combined via an efficient hybrid control scheme, where the PI or PID controller functions as the principal controller for normal operating conditions, while the Fuzzy Logic controller handles specific scenarios or non-linearity. The transition between controllers may be governed by predefined conditions or imprecise rules that evaluate the state or performance criteria of the system.

By integrating these control techniques in the ensemble predictive control model, the proposed method can capitalize on the advantages of each technique to improve the performance of the PV system. The use of PI, PID, and FLC enables the system to manage various operating conditions, enhance tracking accuracy, and reduce the impact of uncertainties and non-linearity, resulting in more efficient and reliable solar PV MPPT deployments.

3.6 Need of VARMA, GRU, and LSTM

The inclusion of the predictive control features through the use of VARMA-GRU and LSTM models in the proposed ensemble predictive control model for solar PV MPPT deployments is essential for the reasons listed below:

- Solar power generation is influenced by a number of variables, including weather conditions, solar irradiance, and demand variations. Traditional control models frequently function in a reactive manner, adjusting based on current measurements or sensor feedback. In contrast, the predictive control function provided by VARMA-GRU and LSTM models enables proactive decision-making. These models are capable of analyzing historical data, identifying patterns, and predicting future trends in power generation. Using these predictions, the control model is able to proactively optimize power generation and load management, resulting in enhanced system performance and efficiency.

3.7 Experimental setup

1. Simulation Environment: The experiments in this work were conducted using MATLAB/Simulation, a widely used simulation environment for system-level modeling and simulation.

2. SEPIC and Controller Simulation: The SEPIC converter and the ensemble predictive control model were simulated in MATLAB/Simulation. The SEPIC converter’s behavior was modeled using circuit equations and control algorithms implemented within Simulation blocks.

3. Converter Parameters: The specific parameters of the SEPIC converter used in the simulations were as follows:

   - Inductor values: \( L_1 = 100 \mu\text{H}, L_2 = 200 \mu\text{H} \)
   - Capacitor values: \( C_1 = 100 \mu\text{F}, C_2 = 220 \mu\text{F} \)
   - Switching frequency: 50 kHz
   - Duty cycle range: 0.2–0.8

4. Ideal Components and Control Laws: In this study, ideal components and control laws were considered to focus on the evaluation of the proposed control scheme’s performance. Non-idealistic, such as component losses and control system imperfections, were not taken into account.

5. PV Model and Solar Data: The simulations utilized the single-diode PV model, a widely used model for simulating PV panel behavior. The model includes parameters such as the short-circuit current \( I_{sc} \), open-circuit voltage \( V_{oc} \), diode ideality factor \( n \), and series and shunt resistances.

Solar data from a particular location were used to represent the solar irradiance and environmental conditions. For example, a solar dataset from the National Renewable Energy Laboratory (NREL) for a specific location could be utilized. Values for different components,
Based on these values different simulation experiments were conducted, and their results are analyzed in the next section of this text.

4 Result in analysis and comparison

The proposed model uses a variety of control mechanisms, such as PID, MPPT, PI, and fuzzy controllers, to control solar PV systems selectively. The optimal parameters and configurations for each control device are found using the proposed bio-inspired optimization technique, resulting in a more thorough and effective method of controlling these devices for various scenarios. Our model includes a predictive control operation that uses a VARMA-GRU with an LSTM model, which can precisely forecast the solar system’s future power generation scenarios. This feature can improve the system’s overall performance for various use cases and enable more effective energy management under different use cases. This model was simulated for different conditions, and values for the Energy Efficiency Ratio, Cost Savings Percentage, Control Signal Smoothness Index, Weighted Performance Index, TS, and Robustness Index were estimated during these simulations. These simulation conditions are described as follows.

It can be observed that the proposed model is able to hold on to maximum power levels as observed in Figure 6, which makes it useful for high-performance applications. This is possible due to the use of high efficiency MPPT selection and control circuits, thereby improving the circuit’s response to varying radiation levels.

It can be observed that the proposed model is able to maintain maximum power levels for different duty cycles as observed from Figure 7, which makes it useful for high-performance applications. This is possible due to the use of the high efficiency VARMA process, which improves the circuit’s response to varying radiation levels.

Due to dynamic changes in duty cycles, the voltage and current levels across the switch are maintained under dynamic load changes. This makes the model highly effective for real-time scenarios observed from Figure 8.

1. Solar Deployment Configuration:
   - Total number of solar panels: 3.
   - Solar panel capacity: 350 watts each.

2. Environmental Data:
   - Solar irradiance: Hourly data for a specific location (e.g., measured or simulated values).
   - Ambient temperature: Hourly data for the same location.

3. Control Parameters:
   - Prediction horizon: 24 h (divided into multiple time steps).
   - Control horizon: 6 h (number of time steps for which control actions are determined).
   - Control intervals: 1 h (time intervals at which control actions are updated).
   - Ensemble size: 5 (number of individual predictive control models in the ensemble).

4. Optimization Algorithm:
   - GWO.
   - Objective functions: Maximize energy generation, minimize cost, and maintain system stability.

5. Simulation Time:
   - Total simulation time: 7 days (168 h).
   - Time step size: 1 h.

6. Performance evaluation metrics:
   - Energy Efficiency Ratio (EER).
   - Cost Savings Percentage (CSP).
   - Control Signal Smoothness Index (CSSI).
   - Weighted Performance Index (WPI).
   - Settling Time (TS).
   - Robustness Index (RI).

7. Comparison Models:
   - Model 1 (M1): Hybrid Predictive Control (HPC) Control [8].
   - Model 2 (M2): Model-Predictive Control (MPC) [4].
   - Model 4 (M4): Finite Control Set-Model Predictive Control (with fixed setpoints) [13].

Based on these conditions, the results were measured for STC (standard Temperature Conditions) and compared with those of the existing models. A sample of these simulation conditions (SCs) mentioned radiation in w/m² and Temperature in °C, and various parametric evaluation metrics such as Energy Efficiency Ratio, Cost Savings Percentage, Control Signal Smoothness Index, Weighted Performance Index, Settling Time (in seconds), and Robustness Index observed in Table 1.

Based on this analysis and Figure 9, it can be observed that the proposed model can improve the energy efficiency by 3–8% when compared with existing models under different simulation conditions. This is possible because on low-complexity feature extraction and optimization models improve the energy performance under different simulation conditions.
Based on this analysis and Figure 10, it can be observed that the proposed model can improve the cost-saving percentage by 4.0–8.5% when compared with existing models under different simulation conditions. This is possible due to the use of GWO for tuning and VARMA for predictive analysis, which assists in improving the cost savings even under different simulation conditions.

Based on this analysis and Figure 11, it can be observed that the proposed model can optimize the CSSI levels by 8.3–10.4% when compared with existing models under different simulation conditions. This is possible due to the use of multiple control models for fine-tuning system outputs, which assist in smoothing the control signal outputs even under different simulation conditions.

Based on this analysis and Figure 12, it can be observed that the proposed model can optimize the WPI levels by 4–18% when compared with existing models under different simulation conditions. This is possible due to the use of multiple control models with VARMA for fine-tuning system outputs, which assist in smoothing control signal outputs and enhancing efficiency levels even under different simulation conditions.

Based on this analysis and Figure 13, it can be observed that the proposed model can reduce the delay needed for the output to settle by 4–15% when compared with existing models under different simulation conditions. This is possible due to using VARMA with LSTM and GRU for fine-tuning system outputs, which assist in faster-settling output levels even under different simulation conditions.
Based on this analysis and Figure 14, it can be observed that the proposed model can improve the robustness index by 3–8% when compared with existing models under different simulation conditions. This is possible due to the use of GWO Optimizations for multiple control units and use of VARMA with LSTM and GRU for fine-tuning system outputs, which assist in faster settling of output levels even under different simulation conditions. Due to these optimizations, the proposed model can be deployed in various real-time scenarios.
5 Conclusion

In this paper, using two bio-inspired optimizations, the author proposed an ensemble predictive control model for solar deployments. The findings show that model performs better than the existing models in terms of energy efficiency improving by 3–8%, cost savings improve by 4–8.5%, optimizing control signal smoothness by 8.3–10.4%, performance index by 4–18%, settling time by 4–15%, and robustness improve by 3–8% under various simulation conditions. Low-complexity feature extraction methods, optimization models like the GWO, and VARMA models for predictive analysis are combined to produce these improvements.

- The necessity for cost-effective solar energy solutions drives this endeavor. As solar deployment grows, advanced control systems that maximize energy output, decrease costs, and ensure system stability are required. We present an ensemble predictive control model that improves solar resource used in different sectors.
- This research affects several disciplines. Solar installations’ environmental effect and sustainability are reduced by our model’s energy efficiency. Energy generation optimization maximizes solar resource usage and reduces dependence on conventional energy.
Second, our model’s cost reductions make solar installations more economically viable for people and enterprises. This may accelerate renewable energy adoption.

- The proposed ensemble predictive control approach offers a broad variety of applications. It may be utilized in utility-scale solar farms, industrial complexes, commercial buildings, and residential solar systems. By improving energy efficiency, cost savings, and resilience, our model helps stakeholders make informed solar system design, operation, and optimization choices.

6 Future work

The proposed ensemble predictive control model for solar deployments will be further improved, validated, and expanded in this paper’s future work. Exciting new opportunities for research and practical applications in the field of solar energy optimization are made possible by the integration of advanced machine learning techniques, hybrid energy systems, energy storage optimization, adaptive control strategies, demand-side management, smart grid technologies, cost-benefit analysis, scalability, and integration with building energy management systems.

Conflict of interest

The authors declare that there is no conflict of interest.

References


