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Hybrid Grey Wolf Optimizer for Efficient Maximum Power Point Tracking to Improve Photovoltaic Efficiency

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Abstract – Today, the demand for Renewable Energy (RE) sources has increased a lot; out of all Renewable Energy Sources (RES), Solar Energy (SE) has emerged as a better solution due to its sustainability and abundance. However, energy sources from the sun directly depend on the efficiency of the photovoltaic (PV) systems employed, whose efficiency depends on the variability of solar irradiance and temperature. So harvesting the maximum output from PV panels requires optimized Maximum Power Point Tracking (MPPT) systems. The traditional MPPT systems that involved Perturb and Observe (P&O) and Incremental Conductance (IncCond) are the most widely used models. However, those models have limited efficiency due to rapidly changing environmental conditions and their tendency to oscillate around the Maximum PowerPoint (MPP). This paper proposes a Hybrid Heuristic Model (HHM) called the Hybrid Grey Wolf Optimizer (HGWO) Algorithm, which employs the Genetic Algorithm (GA) model for optimizing the Grey Wolf Optimizer (GWO) algorithm for effectively utilizing MPPT in PV systems. The simulation decreases fluctuation, boosting how the system responds to shifts in the surrounding atmosphere. The framework evolved through several experiments, and its ability to perform was assessed concerning the results of different models for the factors that were considered seriously throughout several solar radiation and temperature scenarios. During all of the tests, the recommended HGWO model scored more effectively than the other models. This succeeded by accurately following the MPP and boosting the power supply.

Keywords – Renewable Energy Sources, Solar Energy, Machine Learning, Photovoltaic System, Maximum Power Point Tracking, Hybrid Grey Wolf Optimizer, Accuracy.

I. INTRODUCTION

The application of renewable energy sources (RES) has become ever more essential in order to achieve the objective of finding ecologically sound options and fulfilling the demand for energy on a global scale. One of the RESs that is readily accessible, solar energy (SE), is now recognized as the most popular energy source since it is additionally safe and accessible [1]. RES collection depends primarily on photovoltaic, or PV, panels, which are designed to collect SE and produce power. A panacea that can be more predictable and secure to alleviate the issue of dependence on petroleum and natural gas can be found in PV systems, which have the ability to transfer SE into electrical energy. There is a correlation between the volume of SE that is extracted and the degree of effectiveness of PV cells when it comes to harvesting electrical power [2].

The energy production of PV systems, in the opposite conjunction, has a fundamental link to the constant flow of direct sunlight. Energy from sunlight and variations in heat are two of the key elements of SE that have a major effect on the level of electrical energy that produces electricity [3]. Due to the fact that fluctuations of such factors result in a loss in the performance of PV panels, which in turn outcomes in the panels operating at less than their highest possible Maximum Power Point (MPP), that reliance is causing problems with successfully exploiting SE.

For the objective of enhancing the operational effectiveness of PV systems, techniques that are commonly referred to as Maximum Power Point Tracking (MPPT) were designed [4]. It is vital to perform this method in order to put forward an approach for addressing the issue at hand. MPPTs are concepts that have the power to rapidly change the settings of PV panels' function and the electrical power supply. It is essential to execute the above process in order to guarantee that the panels provide efficiency that is nearly identical to the MPP as is feasible in practice, subject to any changes that might happen in outside factors [5].

The MPPT systems have successfully boosted the energy output of PV systems by using this rapid control feature. Because of this, the MPPT model is a vital element for making the most of SE [6]. The conventional MPPT approaches include the Perturb and Observe (P&O) and Incremental Conductance (IncCond) techniques, which were the most commonly employed methods for conducting PV optimization. However, both models suffer from severe drawbacks; as an outcome, they cannot adapt their actions following fast-changing circumstances [7]. Because of this, hypothetical circumstances are the primary factors contributing to losses. A few instances of these scenarios include (i) oscillation in MPP, (ii) delayed response, and iii) problems in tracking amid partial shade conditions. Given these drawbacks, there is an immediate need for more advanced MPPT methods that can provide improved reliability, performance, security, and the capacity to cope with rapidly shifting features such as sunlight and temperature.

A framework that addresses the computational challenge of MPPT in PV systems in fluctuating solar radiation and weather conditions is recommended in this paper. The idea for this study depends on the circumstances mentioned previously. The studies led to the development a novel Hybrid Heuristic Model (HHM) that acquired the name Hybrid Grey Wolf Optimizer (HGWO). This framework emerged using Grey Wolf Optimizer (GWO) principles. The GWO evolved with the social system and predation methods of grey wolves functioning as its main point of reference. The HGWO based on GWO is optimized using Genetic Algorithm (GA) operations that enhance the solution diversity and prevent premature convergence. The proposed model's effectiveness in handling varied Solar Irradiance (SI) and temperature and ensuring high energy productivity was examined using a series of experiments and analysed using metrics such as efficiency, convergence speed, comparative performance, sensitivity, and computational complexity. The results have shown that the HGWO model outperformed both the P&O and IncCond traditional models.

The paper is structured as follows: the literature review is presented in Section 2, Section 3 presents the background, Section 4 presents the methodology, Section 5 presents the results, and Section 6 concludes the work.

II. LITERATURE REVIEW

[8] had been involved in investigating the sensitivity corresponding to MPP related to environmental factors like temperature and irradiance. Their investigation was attributed to their proposal of a novel method that utilized a Machine Learning (ML) model in order to predict the optimum reference voltage factor related to a PV panel under all weather conditions. They have employed the Proportional-Integral-Derivative controller and a DC/DC boost converter for the simulation and analysis of the proposed work. Through the experiment, the work demonstrates the robustness of their model with a Support Vector Machine (SVM) against other models in mixed disturbances.

[9] Their work described the implementation of linear and nonlinear regression-type ML algorithms to operate PV systems at MPP. They demonstrated the effectiveness of different ML models, out of which they showcased the efficiency of regression algorithms, which had better adaptability to the duty cycle of a boost converter than other models, such as beta MPPT and Artificial Neural Network (ANN) approaches and had performed better even in different environment conditions.

In another work by [10], they presented a Decision-Tree (DT) based ML algorithm for MPPT. They attempted this work to exhibit the DTs method's ability to deal with the non-linear data that are generated by dynamic weather conditions. Through multiple experiments through simulation, they have shown that their approach had improved efficiency by around 93.93% in steady-state conditions. They defended their model through these experiments and demonstrated that it has a significant advantage over existing MPPT methodologies.

[11] had proposed a model that uses Slime Mould Optimization (SMO) and an improved Salp Swarm Optimization Algorithm (ISSA) to address the power loss due to irregular irradiance and partial shading. LSA, which refers to local search algorithms, is an approach which assists the SMO-MPPT technique, which is another unique method, to decrease variations.

When contrasted with additional conventional approaches such as P&O and PSO, this method showed superior results in both steady-state and transient scenarios throughout many different environmental variables.

The key goal of their study was to build an architecture that could be applied to tackle the issues that have been brought about by scenarios that include partial shading [12]. In order to discover a fix to this problem, they developed an approach they decided was called Modified Particle-Swarm Optimization (MPSO). Based on the outcomes obtained from their studies and evaluations, their MPSO system was able to produce an important boost in energy usage while continuing to operate at the MPP level on a global level. Employing the mathematical model that they established, they were able to illustrate the boost in overall the use of energy. The algorithm they developed revealed excellent outcomes concerning usefulness as well as accuracy when contrasted with traditional methods and Neural Network (NN) methods [13-15]. This was confirmed by the results of the evaluations that were performed.

III. BACKGROUND

Methods of Maximum Power Point Tracking

P&O

The P&O method is one of the simplest and most commonly used MPPT algorithms. It involves periodically perturbing (adjusting) the voltage (V_{pv}) of the PV module and observing the effect on power output $\left(P_{pv} = V_{pv} \times I_{pv}\right)$. The algorithm decides the direction of the next perturbation based on the change in power (ΔP) resulting from the last perturbation (ΔV).

IncCond

IncCond calculates the derivative of power concerning voltage (dI/dV) and compares it to the rapid conductance ($-I/V$) to find the MPP. The voltage is adjusted until this derivative equal zero, indicating the MPP.

Constant Voltage (CV)

The CV method assumes a fixed relationship between the open-circuit voltage (V_{oc}) and the MPP voltage, setting the operating voltage $\left(V_{op}\right)$ at a predetermined fraction (k) of V_{oc}.

Fuzzy Logic Control (FLC)

FLC uses a set of control rules based on Fuzzy Logic (FL) to adjust the operating point without requiring a precise mathematical model, making it adaptable to changing conditions.

Hybrid Algorithms

Hybrid algorithms combine the strengths of two or more MPPT methods to improve efficiency and accuracy. For example, a system might use P&O for general tracking and switch to IncCond for finer adjustment as it nears the MPP [16-20].

Table 1 presents details about the MPPT techniques.

Table 1. MPPT Techniques

Method	Description	Advantages	Limitations
P&O	Adjusts voltage and observes changes in power to find the MPP.	Simple and easy to implement.	It can oscillate around MPP and is less effective under rapid changes.
IncCond	Determines MPP by equating the conductance to the derivative of power concerning voltage.	More accurate for changing conditions.	It is more complex and can oscillate around MPP.
CV	Sets operating voltage at a fixed fraction of open-circuit voltage.	Simple and effective for stable conditions.	It can be inaccurate if conditions vary.
FLC	Utilizes FL rules to adjust the operating point.	Performs well under variable conditions and is robust to changes.	It requires expert knowledge to design and is computationally intensive.
Hybrid Algorithms	Integrates multiple MPPT methods for better performance.	Improves efficiency and accuracy by combining methods.	It is more complex and can be costlier.

PV Array Modeling

Accurate modelling of the PV array is needed for the practical application of MPPT algorithms. A typical model for a PV cell includes a current source with a parallel diode to capture the nonlinear I-V characteristics, incorporating series and parallel resistances (Rs and Rp) for internal resistive losses and leakage current, respectively.

The current output (I) of a PV cell can be described as EQU (1) and EQU (4).

$$I = I_{ph} - I_0 \left[\text{Exp} \left(\frac{V + I \cdot R_s}{n \cdot V_{th}} \right) - 1 \right] - \frac{V + I \cdot R_s}{R_p} \quad (1)$$

$$I_{ph} = G \cdot A \cdot \eta_{qe} \quad (2)$$

$$I_0 = I_{0,\,\text{ref}} \left(\frac{T}{T_{\text{ref}}} \right)^3 \exp \left(\frac{-E_g}{k} \left(\frac{1}{T} - \frac{1}{T_{\text{ref}}} \right) \right) \quad (3)$$

$$V_{th} = \frac{k \cdot T}{q} \quad (4)$$

where, $'V'$ is the cell output voltage, R_s and R_p are the series and parallel resistances, $'n'$ is the diode ideality factor, $'G'$ is the SI (*W/m²*), A is the area of the PV cell (m^2), η_{qe} is the quantum efficiency of the cell, $I_{0,\,\text{ref}}$ is the reverse saturation current at a reference temperature, T and T_{ref} are the actual and reference temperatures (*Kelvin*), E_g is the bandgap energy of the semiconductor material, $'k'$ is Boltzmann's constant ($1.38 \times 10^{-23}\ \text{J}/K$), $'q'$ is the charge of an electron ($1.6 \times 10^{-19}\text{C}$).

The relationship between the PV voltage (V) and a PV panel's output DC power (P) is illustrated to demonstrate the importance of control systems for tracking the MPP amid varying environmental conditions. These relationships show that SI (G) and cell temperature (T) vary, and the MPP also shifts correspondingly. The following chart in **Fig 1** shows the power variation from a panel compared against varying 'G' and 'T'.

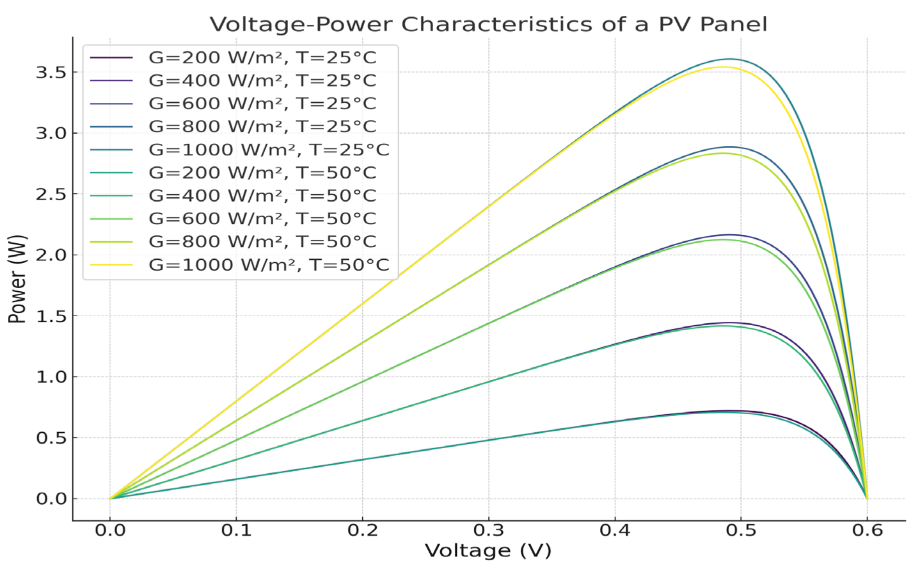

Fig 1. Power Variation of PV Panel.

Problem Definition

The primary objective of this model is defined by the following objective function, which aims to maximize the power output of the PV system by optimizing the voltage and current at the PV module to align with the MPP, EQU (5).

$$\text{Max}P_{PV} = V_{PV} \times I_{PV} \quad (5)$$

Subject to the constraints:

- $0 \leq V_{PV} \leq V_{OC}$, where V_{OC} is the open-circuit voltage.
- $0 \leq I_{PV} \leq I_{SC}$, where I_{SC} is the short-circuit current.

The Hybrid GWO-MPPT algorithm employs the GWO's social hierarchy and predation strategies to search for and converge upon the V_{MPP} and I_{MPP} that maximize P_{MPP}. The algorithm iteratively adjusts V_{PV} and I_{PV}, evaluating the objective function P_{PV} under varying conditions of G and T to ensure that the operating point is always near or at the MPP. The notations used in the objective function are described in the following **Table 2**.

Table 2. Notations Used in This Work

Notation	Description
$\boldsymbol{P_{PV}}$	Power output from the PV module
$\boldsymbol{V_{PV}}$	The voltage across the PV module
$\boldsymbol{I_{PV}}$	Currently, through the PV module
$\boldsymbol{G}$	SI (W/m^2)
$\boldsymbol{T}$	Temperature ($^\circ$C)
$\boldsymbol{V_{MPP}}$	The voltage at the MPP
$\boldsymbol{I_{MPP}}$	Current at the MPP
$\boldsymbol{P_{MPP}}$	MPP
$\boldsymbol{\Delta V}$	Perturbation in voltage
$\boldsymbol{\Delta I}$	Perturbation in current
$\boldsymbol{V_{OC}}$	Open-circuit voltage
$\boldsymbol{I_{SC}}$	Short-circuit current

IV. METHODOLOGY

Introduction to GWO

The GWO algorithm mimics the social hierarchy and hunting behaviour of grey wolves in nature. Grey wolves are animals known to live in packs, typically consisting of about 5 to 12 members. These packs are structured into four hierarchy levels: alpha, beta, delta, and omega wolves; each has a distinct role in the pack's decision-making and hunting strategy. The alpha wolves lead the pack, making movement, hunting, and resting decisions. The beta wolves act as the second in command, generally assisting the alpha in decision-making processes. The delta wolves are subordinate to the alpha and beta wolves, and the omega wolves are considered to have the lowest ranking among all other members of the pack.

The Alpha $(\vec{G}_\alpha)$, beta $(\vec{G}_\beta)$, and delta $(\vec{G}_\delta)$ Wolves represent the best, second-best, and third-best solutions, respectively, while the omega $(\vec{G}_\omega$) Wolves are considered for exploring alternative solutions. The positions are updated according to the following equations, representing the iterative process of prey encirclement and attack strategy, EQU (6) and EQU (7).

$$\vec{G}(t+1) = \vec{G}_p(t) - \vec{A} \cdot \vec{D} \tag{6}$$

$$\vec{D} = \left|\vec{C} \cdot \vec{G}_p(t) - \vec{G}(t)\right| \tag{7}$$

Here, $'t'$ denotes the current iteration, while $\vec{A}$ and $\vec{C}$ are coefficient vectors determining the intensity and direction of the wolves' movement towards the prey, represented by $\vec{G}_p$. The position of a wolf is denoted by $\vec{G}$. The coefficients $\vec{A}$ and $\vec{C}$ are calculated as follows: EQU (8) and EQU (9).

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \tag{8}$$

$$\vec{C} = 2 \cdot \vec{r}_2 \tag{9}$$

The parameter $\vec{a}$ decreases linearly from 2 to 0 throughout the iterations that balance between exploration (searching for prey) and exploitation (homing in on the prey), with $\vec{r}_1$ and $\vec{r}_2$ as random vectors in the range $[0,1]$. The value of $\vec{a}$ is updated using the EQU (10):

$$\vec{a} = 2 - t \cdot \frac{2}{M_t} \tag{10}$$

where M_t is the maximum number of iterations for the optimizer.

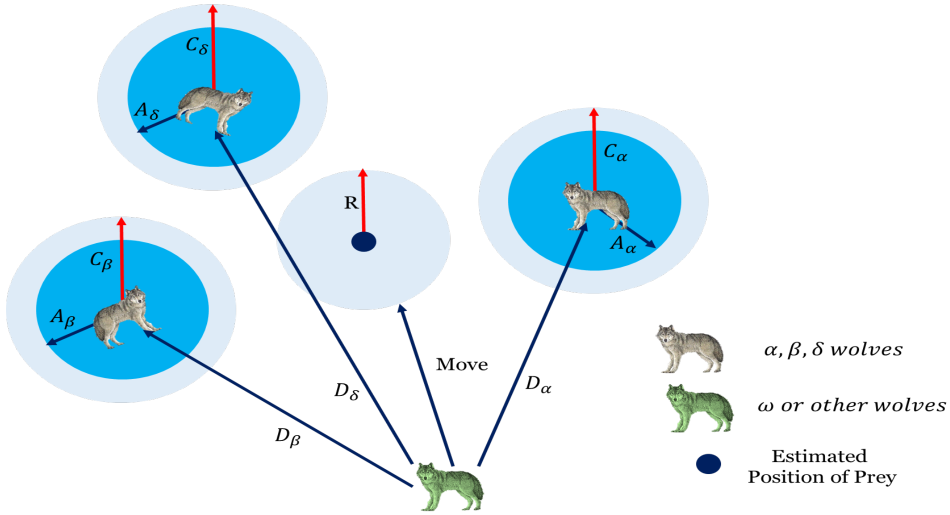

Fig 2. GWO Algorithm's Position Update.

The position update process, as shown in **Fig 2**, involved the calculation of the distance. $(\vec{D}_\alpha, \vec{D}_\beta, \vec{D}_\delta)$ between the prey and each of the three leading wolves (alpha, beta, and delta). These distances are defined by the EQU (11):

$$\begin{aligned}\vec{D}_\alpha &= |\vec{C}_1 \cdot \vec{G}_\alpha - \vec{G}| \\ \vec{D}_\beta &= |\vec{C}_2 \cdot \vec{G}_\beta - \vec{G}| \\ \vec{D}_\delta &= |\vec{C}_3 \cdot \vec{G}_\delta - \vec{G}|\end{aligned} \tag{11}$$

where $\vec{C}_1, \vec{C}_2$, and $\vec{C}_3$ are coefficient vectors. The next step involves updating the positions of the wolves based on the distances calculated from the alpha, beta, and delta wolves, using the following EQU (12):

$$\begin{aligned}\vec{G}_1 &= \vec{G}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha \\ \vec{G}_2 &= \vec{G}_\beta - \vec{A}_2 \cdot \vec{D}_\beta \\ \vec{G}_3 &= \vec{G}_\delta - \vec{A}_3 \cdot \vec{D}_\delta\end{aligned} \tag{12}$$

The final position of the wolf pack $(\vec{G}(t+1))$ at the next iteration is then determined by averaging the positions derived from the alpha, beta, and delta wolves, EQU (13).

$$\vec{G}(t+1) = \frac{\vec{G}_1 + \vec{G}_2 + \vec{G}_3}{3} \tag{13}$$

The Hybrid GWO

The traditional GWO faces challenges such as premature convergence and limited exploration when applied to the dynamic MPPT problem. The HGWO addresses these challenges by integrating GA's crossover and mutation operations into the GWO framework.

Initial Population

The HGWO process starts with a randomly generated population of search agents (wolves) representing potential solutions within the PV system's parameter space. Each agent's position is particularly denoted as $V_i(x)$ which reflect the settings of voltage (V_{PV}) and current (I_{PV}) In order to maximize the power output $(P_{PV} = V_{PV} \times I_{PV})$ of the PV system. The initial positions are determined by the physical limits of the open-circuit voltage (V_{OC}) and short-circuit current (I_{SC}) :

Voltage Initialization $(\boldsymbol{V_{PV}})$

The initial voltage for each agent is randomly selected and lies in the range from 0 to V_{OC}. The expression for initializing the voltage for the $'i'$ agent is given by EQU (14).

$$V_{PV,i} = V_{\min} + \text{rand}\,() \times (V_{OC} - V_{\min}) \tag{14}$$

where $V_{\min}$ is the minimum voltage (close to 0), rand () is a random number between 0 and 1, and V_{OC} is the open-circuit voltage.

Current Initialization $(\boldsymbol{I_{PV}})$
The initial current for each agent is randomly determined within the range from 0 to I_{SC} and the expression for initializing the current for the $'i'$ agent is denoted by EQU (15).

$$I_{PV,i} = I_{\min} + \text{rand}\,() \times (I_{SC} - I_{\min}) \tag{15}$$

where $I_{\min}$ is the minimum current, rand () is a random number between 0 and 1, and I_{SC} is the short-circuit current.

Fitness Function Definition
The Fitness Function (Fit) aims to minimize the deviation between the actual power output of the PV system and the maximum power output possible under the current environmental conditions. This is represented as EQU (16).

$$\text{Fit}\,(V_{PV}, I_{PV}) = \frac{1}{1+|P_{actual} - P_{MPP}|} \tag{16}$$

where, P_{actual} represents the actual power output, P_{MPP} is the maximum power output; the objective is to maximize this Fit by finding the V_{PV} and I_{PV} values that minimize the absolute deviation$|P_{actual} - P_{MPP}|$. Since the Fit is the inverse of this deviation, maximizing the Fit corresponds to minimizing the deviation, effectively aligning the PV system's operating point with the MPP.

The HGWO uses this Fit to guide the search for optimal V_{PV} and I_{PV} settings. During the optimization process, the wolves (search agents) explore the solution space of V_{PV} and I_{PV} values, guided by the Fit towards configurations that produce power outputs closer to P_{MPP}. Through iterations involving crossover and mutation aimed at enhancing exploration and exploitation of the solution space, HGWO aims to identify the set of V_{PV} and I_{PV} that maximizes Fit (V_{PV}, I_{PV}), thereby ensuring the PV system operates as close to the MPP as possible given the current environmental conditions.

Crossover
In the crossover stage, two selected solutions, a parent solution (P_s) and a neighbouring solution (N_s), are merged to produce one or more offspring solutions. The offspring inherit characteristics from both parent solutions, enriching the solution space with new variants. This process is governed by the crossover operation, mathematically represented as EQU (17).

$$O_i = \lambda \cdot P_s + (1 - \lambda) \cdot N_s \tag{17}$$

where,

- O_i is the offspring solution produced from the crossover operation.
- $P_s = \left[V_{PV}^{P_s}, I_{PV}^{P_s}\right]$ and $N_s = \left[V_{PV}^{N_s}, I_{PV}^{N_s}\right]$ The parent and neighbouring solutions are a vector of voltage and current settings.
- λ is a random crossover factor within the range $[0,1]$ that determines the degree to which the offspring inherits characteristics from each parent.

Mutation:
Mutation in the HGWO is applied to individual solutions (wolves) to introduce random changes in their V_{PV} and I_{PV} settings. The mutation operation can be mathematically represented as follows for a given solution S_i, EQU (18).

$$S_i' = S_i + \mu \cdot (S_{\text{rand}} - S_i) \tag{18}$$

where:

- S_i' is the mutated solution.
- $S_i = \left[V_{PV}^{S_i}, I_{PV}^{S_i}\right]$ is the original solution before mutation.

- μ is the mutation rate, a randomly chosen factor within the range $[0,1]$ that determines the extent of mutation applied to the solution.
- $S_{\text{rand}} = \left[V_{PV}^{S_{\text{rand}}}, I_{PV}^{S_{\text{rand}}}\right]$ is a randomly selected solution from the population that serves as the reference for presenting variation. This selection ensures that the mutation introduces a directed randomness, potentially guiding the solution towards unexplored areas of the solution space.

The choice of S_{rand} is critical, as it influences the direction and magnitude of the mutation. The goal is to use S_{rand} to push S_i towards potentially more optimal V_{PV} and I_{PV} settings that have not yet been considered by S_i, thereby expanding the exploration of the solution space.

Exploitation Phase

In the exploitation phase, the positions of the wolves within the packet are adjusted to converge towards the best solutions represented by the alpha, beta, and delta wolves. These changes are guided by the following expressions, which explicitly calculate the contribution of each leading wolf, EQU (19) and EQU (20).

$$V_{PV}^{\text{new}} = \frac{1}{3}\left(V_{PV}^{\alpha} + V_{PV}^{\beta} + V_{PV}^{\delta}\right) + A \cdot \left(V_{PV}^{\text{target}} - V_{PV}^{\text{current}}\right) \tag{19}$$

$$I_{PV}^{\text{new}} = \frac{1}{3}\left(I_{PV}^{\alpha} + I_{PV}^{\beta} + I_{PV}^{\delta}\right) + A \cdot \left(I_{PV}^{\text{target}} - I_{PV}^{\text{current}}\right) \tag{20}$$

where:

- V_{PV}^{new} and I_{PV}^{new} are the updated voltage and current settings for a given wolf aimed at moving closer to the MPP.
- $V_{PV}^{\alpha}, V_{PV}^{\beta}$, and V_{PV}^{δ} (similarly for I_{PV}) represent the voltage (current) settings of the alpha, beta, and delta wolves, respectively. These settings are considered the best current estimates for achieving the MPP.
- V_{PV}^{target} and I_{PV}^{target} refer to the hypothetical, optimal settings towards which the pack should converge based on environmental conditions (G and T) and the characteristics of the PV system.
- V_{PV}^{current} and I_{PV}^{current} are the current settings of the wolf being updated.
- A is a coefficient modulates the adjustment based on the distance to the target settings, potentially incorporating random elements to maintain exploration capabilities.

Additionally, the impact of the top wolves can be mathematically represented by incorporating weighted averages where the weights could reflect the relative performance or fitness of the alpha, beta, and delta solutions, EQU (21) and EQU (22).

$$V_{PV}^{\text{new}} = w_{\alpha} \cdot V_{PV}^{\alpha} + w_{\beta} \cdot V_{PV}^{\beta} + w_{\delta} \cdot V_{PV}^{\delta} \tag{21}$$

$$I_{PV}^{\text{new}} = w_{\alpha} \cdot I_{PV}^{\alpha} + w_{\beta} \cdot I_{PV}^{\beta} + w_{\delta} \cdot I_{PV}^{\delta} \tag{22}$$

where, w_{α}, w_{β}, and w_{δ} are weights assigned based on the fitness or rank of each top wolf, with higher weights given to solutions closer to the MPP. This ensures that the packet's direction is prejudiced more by the wolves with the best solutions. The entire process is presented in the algorithm 1.

Algorithm 1 for HGWO for MPPT Input

- G : SI
- T : Temperature
- V_{OC} : Open-circuit voltage
- I_{SC} : Short-circuit current

Output: Optimal V_{PV} and I_{PV} settings to maximize P_{PV}

Procedure:

- **Initialize:** Generate an initial population of N wolves (search agents), where each wolf $'i'$ has a position $W_i = \left[V_{PV,i}, I_{PV,i}\right]$ initialized within the ranges $[0, V_{OC}]$ for voltage and $[0, I_{SC}]$ for current.
- **Evaluate Fitness:** For Each wolf i, calculate the fitness $Fit_i\left(V_{PV,i}, I_{PV,i}\right)$ based on the deviation from the theoretical maximum power point (MPP), considering current G and T.

3 **Iterate Until Convergence:**

- **For Each** iteration t :

  a. Crossover:

- Select pairs of parent wolves (P_s and N_s) based on fitness.
- Perform crossover to generate offspring O_i, where $O_i = \lambda \cdot P_s + (1 - \lambda) \cdot N_s$, and λ is a random factor [0,1].

b. Mutation: For each wolf S_i, apply mutation to introduce random variations: $S_i' = S_i + \mu \cdot (S_{\text{rand}} - S_i)$, where μ is the mutation rate [0,1], and S_{rand} is a randomly chosen solution from the population.
c. Evaluate Fitness: Recalculate the fitness of all wolves, including the newly generated offspring, based on their V_{PV} and I_{PV} settings.
d. Update Positions (Exploitation): Adjust the positions of all wolves towards the best solutions (α, β, δ) based on their fitness, using weighted averages to guide the packet closer to the MPP.
e. Select Alpha, Beta, and Delta: Identify the top three wolves with the highest fitness to serve as α, β, and δ for the next iteration.

- **Termination:** The algorithm terminates when a predefined number of iterations are completed or when the change in fitness between iterations falls below a threshold, indicating convergence.

5 **Output:** Return the voltage (V_{PV}) and current (I_{PV}) Settings of the alpha wolf (α) as the optimal solution for the MPPT problem under the given G and T.

V. EXPERIMENTAL ANALYSIS

To demonstrate the enhancements brought about by implementing AI-based methods for MPPT, we utilized a grid-connected PV model tailored to our experimental setup. The foundation for this model was adapted from a modified version of the 250 *kW* grid-connected PV array model in MATLAB. The configuration consisted of 8 parallel strings, each including 48 series-connected panels of the type LG 400. The comprehensive system integrates a PV array with a boost converter, an inverter, and a connection to the grid. The heart of our experiment lies in the control system designed for MPPT purposes, which finely tunes the duty cycle to modulate the PV voltage, guiding it towards the optimal operating point for maximized efficiency. The proposed model was compared against P&O and IndCond, and the findings are discussed below:

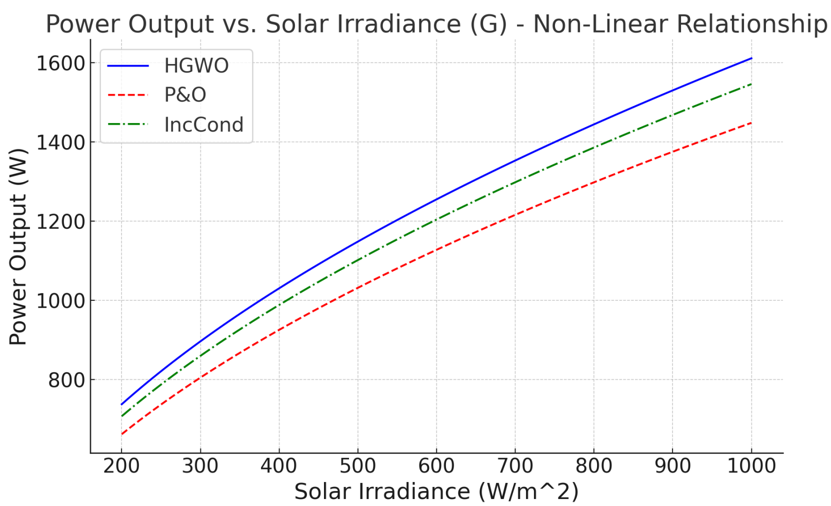

Fig 3. Power Output Vs SI

The chart in **Fig 3** showcases the relationship between Power Output and SI (G) for different MPPT methods. As the SI level increases, it is observed that all three MPPT methods have demonstrated an increase in power output. The HGWO method has shown that it consistently delivers a higher power output across the entire range of SI than the traditional P&O and IncCond methods. The results prove that the HGWO paradigm can more effectively optimise the power generated by PV systems. PV systems are particularly successful when the level of solar radiation fluctuates within the surroundings. This is because of the hybrid composition of the approach, which combines components from the GWO enhanced with features from the genetic algorithms for more effective search and extraction. The improved efficiency of the recommended approach can be identified as the ability of the model to evolve more, which is caused by the hybrid of the natural world of the framework. Following the research results, the P&O method has a lower volume of energy, while the IncCond technique performs higher than the P&O technique but remains less successful than the HGWO technique.

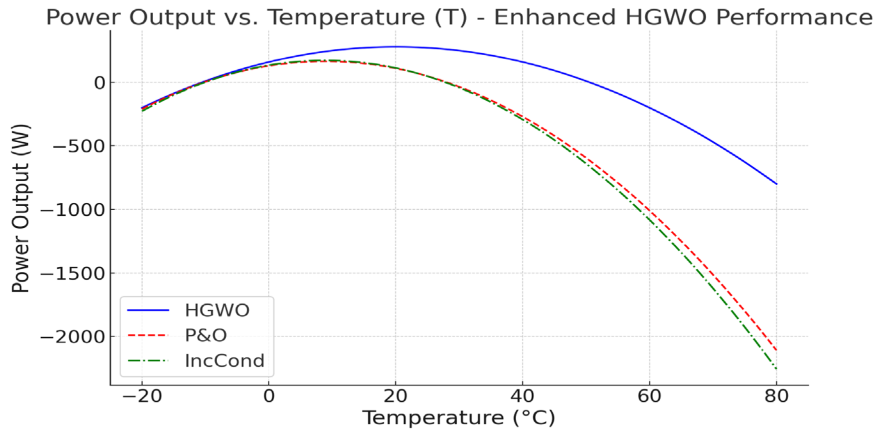

Fig 4. Power Output VS Temperature.

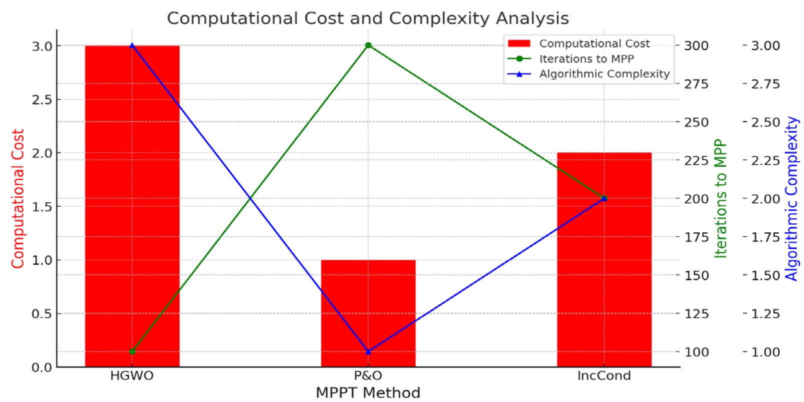

Fig 5. Computation Cost Vs Complexity Vs Iterations to MPP.

Fig 4 shows the power output vs temperature (T) relationship performance of the HGWO compared to the P&O and IncCond methods. The HGWO method has shown a higher peak power output and slower decline when the temperature increases. The proposed HGWO, through the results, have shown better performance for different ranges of temperatures. The graph also shows the outperformance of the proposed model against the P&O and IncCond for varied temperature conditions. **Fig 5** compares computational cost and complexity for the HGWO, P&O, and IncCond MPPT methods. It compares the iterations needed for the model to achieve the MPP; from the results, the proposed model shows a clear picture of its efficiency by taking a smaller count of iterations to reach MPP, which is the main objective of the work. However, it had increased computational cost and complexity compared to the traditional models. This is acceptable due to the nature of the algorithm. The P&O model has the lowest computational cost and complexity but poor performance for MPP. At the same time, the ACO model is next to the HGOA model.

VI. CONCLUSION AND FUTURE WORK

This study is involved in the process of exploring the possibilities for optimization of Maximum Power Point Tracking (MPPT) in photovoltaic (PV) systems. This work has introduced the innovative Hybrid Grey Wolf Optimizer (HGWO) model as a potential solution to the objective of enhancing the adaptability and efficiency of Solar Energy (SE) harnessing. In simulations, the HGWO model demonstrated better performance by employing a model that dynamically track the Maximum Power Point (MPP). When compared to traditional MPPT methods such as Perturb and Observe (P&O) and Incremental Conductance (IncCond), the proposed model performed better even in varied conditions. The comparative analysis has also revealed that the proposed HGWO method outperformed the conventional MPPT techniques that had shown convergence much faster to the MPP by minimizing the oscillations and effectively adapting to rapid environmental changes.

This work presented a novel MPPT optimization model for PV systems that had to provide new avenues for future research to explore its integration with other Renewable Energy (RE) methods.

Data Availability
No data was used to support this study.

Conflicts of Interests
The author(s) declare(s) that they have no conflicts of interest.

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Competing Interests
There are no competing interests.

References

[1]. F. Chien, H. W. Kamran, G. Albashar, and W. Iqbal, "Dynamic planning, conversion, and management strategy of different renewable energy sources: A Sustainable Solution for Severe Energy Crises in Emerging Economies," International Journal of Hydrogen Energy, vol. 46, no. 11, pp. 7745–7758, Feb. 2021, doi: 10.1016/j.ijhydene.2020.12.004.
[2]. S. Dixit, "Solar technologies and their implementations: A review," Materials Today: Proceedings, vol. 28, pp. 2137–2148, 2020, doi: 10.1016/j.matpr.2020.04.134.
[3]. C. Sun, Y. Zou, C. Qin, B. Zhang, and X. Wu, "Temperature effect of photovoltaic cells: a review," Advanced Composites and Hybrid Materials, vol. 5, no. 4, pp. 2675–2699, Aug. 2022, doi: 10.1007/s42114-022-00533-z.
[4]. D. Díaz Martínez, R. Trujillo Codorniu, R. Giral, and L. Vázquez Seisdedos, "Evaluation of particle swarm optimization techniques applied to maximum power point tracking in photovoltaic systems," International Journal of Circuit Theory and Applications, vol. 49, no. 7, pp. 1849–1867, Mar. 2021, doi: 10.1002/cta.2978.
[5]. R. B. Bollipo, S. Mikkili, and P. K. Bonthagorla, "Critical Review on PV MPPT Techniques: Classical, Intelligent and Optimisation," IET Renewable Power Generation, vol. 14, no. 9, pp. 1433–1452, Jun. 2020, doi: 10.1049/iet-rpg.2019.1163.
[6]. S. A. Mohamed, M. A. Tolba, A. A. Eisa, and A. M. El-Rifaie, "Comprehensive Modeling and Control of Grid-Connected Hybrid Energy Sources Using MPPT Controller," Energies, vol. 14, no. 16, p. 5142, Aug. 2021, doi: 10.3390/en14165142.
[7]. "Hybrid, optimization, intelligent and classical PV MPPT techniques: Review," CSEE Journal of Power and Energy Systems, 2020, doi: 10.17775/cseejpes.2019.02720.
[8]. Maximum Power Point Tracking with Regression Machine Learning Algorithms for Solar PV systems," International Journal of Renewable Energy Research, no. Vol12i3, 2022, doi: 10.20508/ijrer.v12i3.13249.g8517.
[9]. Mahesh, P. V., Meyyappan, S., & Alal, R. (2022). Maximum power point tracking with regression machine learning algorithms for solar PV systems. International Journal of Renewable Energy Research, 12(3), 1327-1338.
[10]. P. V. Mahesh, S. Meyyappan, and R. R. Alla, "Maximum power point tracking using decision-tree machine-learning algorithm for photovoltaic systems," Clean Energy, vol. 6, no. 5, pp. 762–775, Oct. 2022, doi: 10.1093/ce/zkac057.
[11]. A. F. Mirza, M. Mansoor, K. Zhan, and Q. Ling, "High-efficiency swarm intelligent maximum power point tracking control techniques for varying temperature and irradiance," Energy, vol. 228, p. 120602, Aug. 2021, doi: 10.1016/j.energy.2021.120602.
[12]. A. Ibrahim et al., "PV maximum power-point tracking using modified particle swarm optimization under partial shading conditions," Chinese Journal of Electrical Engineering, vol. 6, no. 4, pp. 106–121, Dec. 2020, doi: 10.23919/cjee.2020.000035.
[13]. A. M. Vyas and G. S. Kushwah, "Sand Battery: An Innovative Solution for Renewable Energy Storage (A Review)," 2023 IEEE Renewable Energy and Sustainable E-Mobility Conference (RESEM), May 2023, doi: 10.1109/resem57584.2023.10236319.
[14]. V. S. Simankov, P. Yu. Buchatskiy, S. V. Teploukhov, A. N. Cherkasov, and S. V. Onishchenko, "Designing an Intelligent Information and Analytical System for Evaluating Solutions in Renewable Energy Based on Digital Twins," 2023 Seminar on Information Systems Theory and Practice (ISTP), Nov. 2023, doi: 10.1109/istp60767.2023.10426987.
[15]. I. S. Rafiqi and A. H. Bhat, "Role of UPQC In Addressing Power Quality Issues in the Power Grid Connected with Renewable Energy Sources," 2022 1st International Conference on Sustainable Technology for Power and Energy Systems (STPES), Jul. 2022, doi: 10.1109/stpes54845.2022.10006596.
[16]. F. AYADI, I. COLAK, I. GARIP, and H. I. BULBUL, "Targets of Countries in Renewable Energy," 2020 9th International Conference on Renewable Energy Research and Application (ICRERA), Sep. 2020, doi: 10.1109/icrera49962.2020.9242765.
[17]. C. Yuan and X. Xiao, "A unified access conditioner for microgrid with renewable energy sources," 2014 IEEE Energy Conversion Congress and Exposition (ECCE), Sep. 2014, doi: 10.1109/ecce.2014.6953653.
[18]. S. Paul, T. Dey, P. Saha, S. Dey, and R. Sen, "Review on the development scenario of renewable energy in different country," 2021 Innovations in Energy Management and Renewable Resources(52042), Feb. 2021, doi: 10.1109/iemre52042.2021.9386748.
[19]. M. A. Abdulgalil, M. Ali, F. S. Al-Ismail, and M. Khalid, "One-Step Solution for Sizing and Allocation of Battery Energy Storage System Using DC Optimal Power Flow," 2022 11th International Conference on Renewable Energy Research and Application (ICRERA), Sep. 2022, doi: 10.1109/icrera55966.2022.9922869.
[20]. A. M. Mohammad, O. A. Alghamdi, A. A. Alhusssainy, M. Rawa, A. M. Abusorrah, and Y. A. Al-Turki, "Optimal Economic Dispatch of Power System Networks with Renewable Energy Sources," 2023 IEEE PES Conference on Innovative Smart Grid Technologies - Middle East (ISGT Middle East), Mar. 2023, doi: 10.1109/isgtmiddleeast56437.2023.10078642.