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An Efficient Short-Term Solar Power Forecasting by Hybrid WOA-Based LSTM Model in Integrated Energy System

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Abstract

Objectives: Due to the irregular nature of sun irradiation and other meteorological conditions, solar power generation is constantly loaded with risks. When solar radiation data isn't captured and sky imaging equipment isn't available, improving forecasting becomes a more difficult endeavor. So our objective to improve the forecasting accuracy for next year solar power generation data. **Methods:** Our research used a real numerical solar power dataset of Australia and Germany and a standard approach for preprocessing. The feature selection in this research uses the Whale Optimization Algorithm (WOA). A Long Short-Term Memory (LSTM) method is utilized to determine the accuracy of solar power forecasts. The HHO (Harris Hawks Optimization) technique is also used to improve solar power forecasting accuracy. The performances were analyzed and the proposed method is employed in the python platform. **Findings:** The findings show that the suggested technique considerably increases the accuracy of short-term solar power forecasts for proposed method is 3.07 in comparison of LSTM and SVM at different data types and 15 min and 60 min interval. **Novelty:** The key novelties of this research is hybrid strategy for improving the precision of solar power forecasting for short periods of time. Including the Whale Optimization Algorithm (WOA), Long Short-Term Memory (LSTM), and Harris Hawks Optimization (HHO).

Keywords: Power generation; Solar power forecasting; Whale optimization algorithm; Long ShortTerm Memory; Harris hawk's optimization

1 Introduction

Nowadays, solar power generation has increased significantly compared to other types of renewable energy. Natural variations, on the other hand, make solar energy production unstable[(1)]. When it comes to bringing this unexpected renewable energy into the system, solar electricity forecasting is a major challenge[(2)]. The more volume of integration, the more volatile the system gets. If this unstable energy is not efficiently managed, problems with power supply reserve and frequency management will arise. To address these difficulties, very accurate forecasting far in advance will allow us to offer enough electricity to meet current demand while maintaining frequency stability in the system [3]. A multitude of factors, including the algorithm utilized, influence the forecasting model's accuracy [4].

In most cases, a deep learning algorithm is used to convert weather data into power in solar power forecasting models [5]. Because solar power sources are found in a range of locations and have varied capacities, small generating sources frequently do not have weather surveillance systems because it does not cost viable. A major roadblock to solar power being connected to the grid, as well as a power sector prejudice against PV system deployment [6]. As a result, precise short-term forecasting and enhancing the accuracy of solar power forecasts are critical for successfully integrating PV systems into the grid [7]. This gets more challenging if no previous data on solar radiation was acquired and there is no equipment is available for specific sky imaging [8,9].

To enhance solar power forecasting accuracy, the HHO (Harris Hawks Optimization) technique is applied [10]. HHO is a natural-inspired optimization technique based on Harris Hawk behavior modeling. The heart of the algorithm is built on hawks cooperating to catch their prey. This strategy is used by a group of Harris hawks to attack the target from diverse directions, catching it off guard. The accuracy of our proposed work is compared to that of other processes to show that it is superior to those techniques, and the results of the comparison are analyzed.

Liu et al., [4] have presented A simplified LSTM neural network for one-day-ahead solar power forecasting. This work introduces a simpler LSTM algorithm for forecasting one-day-ahead solar power generation based on the architecture of the Machine Learning technique. Under varied weather circumstances, the LSTM model's forecast can successfully capture intra-hour ramping.

Wang et al., [11] have presented a Photovoltaic power forecasting-based LSTM-Convolutional Network. This research proposes and uses a hybrid deep learning model (LSTM-Convolutional Network) to anticipate renewable energy. LSTM-convolutional network technology is used. The proposed hybrid types outperform shows the Convolutional-LSTM Network and the hybrid prediction model outperforms the solar prediction model.

Yu et al., [12]. Have discussed An LSTM short-term solar irradiance forecasting under complicated weather conditions. An LSTM-based approach is employed in this work to produce short-term forecasts using a timeline that incorporates global horizontal irradiance (GHI) one hour and one day ahead of time. The long short-term memory (LSTM) network is the deep structure of RNN. Low loss and pollution feature significantly ease the energy-environment conflict, making it a vital component of the future energy system.

Wang et al., [13]. A day-ahead PV power forecasting technique based on the LSTM-RNN model has been provided, as well as temporal correlation modification in a framework for forecasting daily. Under partial daily basis prediction, a day-ahead PV power prediction approach was devised, based on the LSTM-RNN model and temporal correlation modification. Under the suggested PDPP architecture, the forecasting model's output was further improved for those days with correct daily pattern predictions if time correlation alteration (TCM) is more exact than the specific LSTM-RNN model.

Li et al., [14]. Deep learning with a hybrid component has been presented for solar forecasting in the short term. The wavelet packet degradation process (WPD) & LSTM networks are used in this study to create a hybrid deep learning model. The original solar power series is broken down into sub-series using WPD. Then, for each of these sub-series, four distinct LSTM networks are built. Traditional solar power forecasting methods can't provide the level of precision necessary for energy systems. Some researchers are using deep learning algorithms to enhance the accuracy of projections for solar power or other keys elements to consider when forecasting

Abdel-Nasser et al., [5]. Exact solar power estimating models depend on deep learning algorithms such as LSTM-RNN- which have been reported. This study proposes the need for a long short-term memory recurrent neural network (LSTM-RNN) to correctly predict the output power for PV systems. When LSTM is used instead of other approaches, the predicting error is reduced even more. The proposed forecasting method could be useful for smart grid planning and control.

Hossain et al., [15]. We've talked about using an LSTM neural network to forecast short-term photovoltaic electricity and creating a synthetic weather forecast. This research proposes a forecasting strategy for photovoltaic (PV) power generation utilizing the LSTM neural network (NN). To verify the superiority of the LSTM NN with the proposed features, other deep learning engines such as the RNN, generalized regression neural network, and extreme learning machine are investigated.

Aslam et al., [16]. A two-stage focus on LSTM and Bayesian optimization have been presented for day-ahead solar energy forecasting. The proposed deep-learning technique for forecast PV power for the next day is based on a 2-stage mechanism of attention on the LSTM model. Forecasting for the next day, the proposed models were tested to state-of-the-art methods like LSTM-Attention, CNN-LSTM, and Ensemble models. Some faults in the work will need to be addressed in future research. Over LSTM, there are two layers of attention in the suggested model, each having decoder-encoder layers. In comparison to existing models, this technique used many layers and parameters to be learned.

Zhou et al.,[17]. Short-term PV power forecasting was demonstrated utilizing a long short-term memory neural network and an attention mechanism. A time-series hybrid ensemble deep learning framework for predicting short-term PV power generation is presented in this paper. The temperature is predicted by one LSTM neural network, while the power output is predicted by the other. Predicting data is flattened & mixed with such a layer that is fully connected to increase forecasting accuracy.

This study has the following gaps that are identified and to fill this gap-

- To provide the short term solar power forecasting model based on effective feature selection method that is not used in the literature.
- In our finding Short term PV power that is 15 min and 60 min interval is used which is not used in this study.
- We used a three year solar power datasets to next year power forecasting.
- The HHO (Harris Hawks Optimization) technique is also used to improve solar power forecasting accuracy.

2 Methodology

This study used a standardized approach for preprocessing a real-numerical solar power datasets. Feature selection in this research uses the Whale Optimization Algorithm. The enhanced LSTM method is used to determine the accuracy of solar forecasts shown in Figure 1. HHO (Harris Hawks Optimization) technique is also used to improve solar power forecast accuracy.

2.1 Data Collection

The Austria and Germany countries data sets are utilized in the solar power forecasting. Each of these countries is taken across two time periods, with the first period lasting 15 minutes and the second lasting 60 minutes. Using the two nations mentioned above, the same time frame.

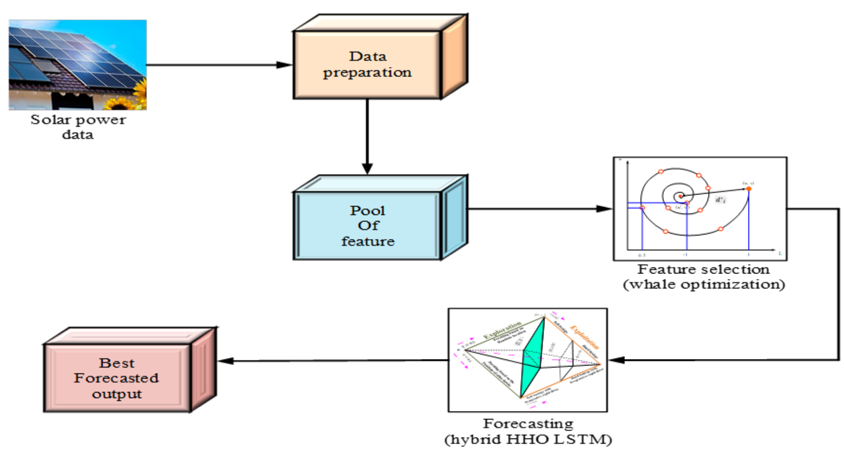

Fig 1. Solar power forecasting in the short-term using a hybrid WOA-based LSTM model

2.2 Whale Optimization Algorithm

The proposed method's inspiration is initially explored in this section. Then there's the mathematical model.

2.2.1 Mathematical model and optimization algorithm

This section introduces a mathematical model for surrounding prey, spiral bubble-net feeding technique, & prey search. Following that, the WOA algorithm is suggested.

2.2.2 Encircling prey

Humpback whales are capable of detecting prey & encircling it. A WOA technique implies that the current best candidate solution would be the goal target as well as extremely close to it since the position of an optimum design within the search space is unknown. Those specific search agents can attempt to enhance overall positions in comparison to other search agents, as determined by the best solution found. This behavior is represented by the equations below:

$$\underset{R}{\rightarrow} = \left| \underset{Q}{\rightarrow} \cdot \underset{u}{\rightarrow} * (t) - \underset{u}{\rightarrow} (t) \right| \quad (1)$$

$$\underset{u}{\rightarrow} (t + 1) = \underset{u}{\rightarrow} * (t) - \underset{P}{\rightarrow} \cdot \underset{R}{\rightarrow} \quad (2)$$

Where,

t is the current iteration, $\overrightarrow{P}$ and $\overrightarrow{Q}$ coefficient vectors,

u' is the position vector of the best solution identified,

$\underset{u}{\rightarrow}$ indicates the position vector,

| | is the exact value and is a Multiplication of elements one by one It's worth noting that u' must be changed in every cycle if a better option is discovered. The vectors P and Q are calculated as follows:

$$P = 2 \underset{i}{\rightarrow} \cdot \underset{r}{\rightarrow} - \underset{i}{\rightarrow} \quad (3)$$

$$Q = 2.r \quad (4)$$

where $\underset{d}{\rightarrow}$ is reduced linearly from two to zero throughout iterations (in both exploration and exploitation phases) and $\underset{r}{\rightarrow}$ is a random vector in (0,1).

The reasoning behind Equation (2) for a 2D situation is shown in Figure 2 (**2a**). A search agent's location (u, v) depends on the location, it's possible to change the current perfect recorded (u', v'). Changing the values of the variables $\underset{P}{\rightarrow}$ and $\underset{Q}{\rightarrow}$ vectors For the current position, there are many areas throughout the country where the best agents can be found. Figure 2 also depicts a search agent's possible updated position in 3D space in Figure 2 (**2b**). It should be noted that by defining the random vector $\underset{r}{\rightarrow}$, any position in the search space between the key points depicted in Figure 2 can be reached. An agent used for searching might update his position inside the region of both the current best answer and the next best solution as a consequence of the Equation (2), emulating the behavior of nearby prey. In a search area with n-dimensional space, the search agents will roam in hypercubes all around the best solution identified.

2.2.3 Exploitation phase (Bubble-net attacking method)

There have been two methodologies created to statistically measure humpback whale bubble-net behavior:

1. Encircling mechanism shrinking: In Equation (3), accomplished by reducing the range of I. It's important to note that i reduce the rate of ((p)) volatility. Where, $\underset{P}{\rightarrow}$ denoted the random number between [-i, i] with i dropping from 2 to 0 with each repetition. The new location of the search agent can be found somewhere between the beginning place and the current best agents using random integers for $\underset{P}{\rightarrow}$ in [-1, 1]. In a 2D space, Figure 2**(3a)** displays the possible positions that $0 \leq P \leq 1$ can accomplish from (u, v) to (u', v').

2. Spiral updating position: This approach begins with computing the distance here between the whale (u, v) and the prey (u', v'), as illustrated in Figure 2**(3b)**. To emulate the A spiral equation is formed between both the position of the whale and the place of the prey due to the helical structure movement of humpback whales:

$$\underset{u}{\rightarrow} (t+1) = \underset{R'}{\rightarrow} \cdot e^{bl} \cdot \, cos2\pi l + \underset{u'}{\rightarrow} (t) \quad (5)$$

where $\underset{R'}{\rightarrow} = \left| \underset{u'}{\rightarrow} (t) - \underset{u}{\rightarrow} (t) \right|$ and denotes a distance between ith whale as well as the prey (currently the best answer), b is indeed a constant used to define the form of a logarithmic spiral, l is a random number in [1,1], and is an element-by-element multiplication.

While swimming, grey whales swim in a lowering circle around their food in a spiral pattern. We assume there's a 50/50 chance of either employing the shrinking encircling mechanism or the spiral model to update whale locations during optimization to simulate this simultaneous behavior. The following is the mathematical model:

$$\overrightarrow{u}\ (t+1) = \begin{cases} \overrightarrow{u} * (t) - \overrightarrow{P}.\overrightarrow{R} & if\ P < 0.5 \\ \overrightarrow{R'}.e^{bl}.\cos 2\pi l + \overrightarrow{u}'(t) & if\ P \geq 0.5 \end{cases} \quad (6)$$

p indicates random integer between [0,1].

Humpback whales hunt for food at random times, in addition to employing bubble nets. The following is the mathematical model for the search.

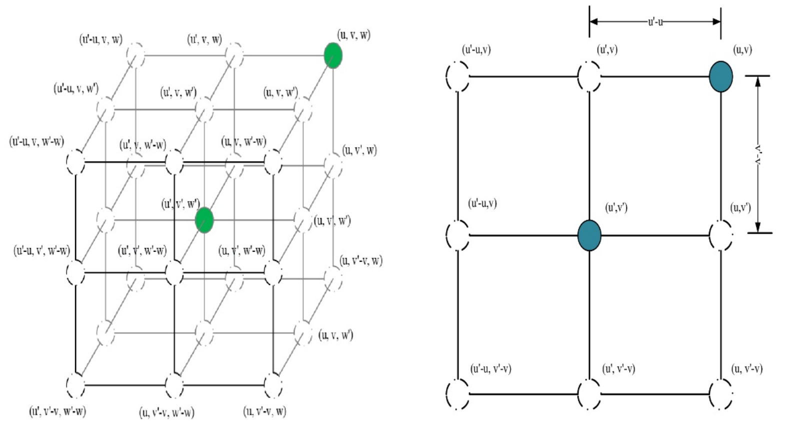

Fig 2(a): 2D position vectors & their likely future positions (the best solution so far is u')

Fig 2(b): 3D position vectors & their potential future positions (u' represents the best answer so far)

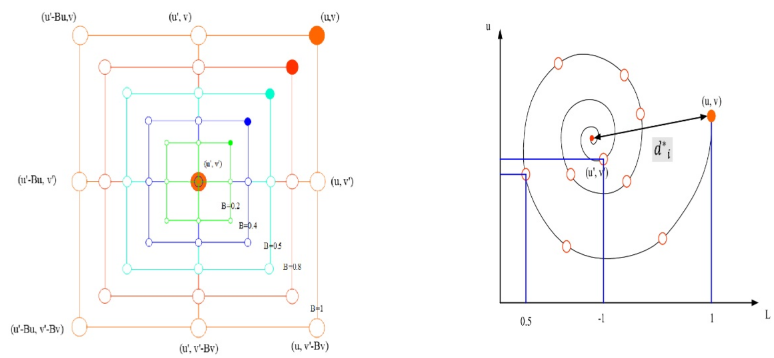

Fig 3 (a): WOA employs the bubble-net search approach (u' seems to be the best answer this far): a shrinking circumferential mechanism

Fig 3(b): WOA employs the bubble-net search method (u' being the best response this far): The spiral update's location

Fig 2. 2 D and 3 D position and Bubble net method

2.2.4 Exploration phase (Search for prey)

A similar strategy that involves changing the B vector can be used to locate prey. In reality, based on their relative locations, humpback whales seek at random. As a consequence, we use B to move the search agent away from the reference whale by using random values larger than or equal to 1. Rather than employing the best search agent identified so far, we utilize a randomly generated search agent that can adjust the position of a search agent throughout the exploration phase. That strategy, combined with the fact that |B| > 1, The mathematical model looks like this:

$$\underset{R}{\rightarrow} = \left| \underset{Q}{\rightarrow} \cdot \underset{u_{rand}}{\longrightarrow} - \underset{u}{\rightarrow} \right| \tag{7}$$

$$\underset{u}{\rightarrow}(t+) = \underset{u_{rand}}{\longrightarrow} - \underset{P}{\rightarrow} \cdot \underset{R}{\rightarrow} \tag{8}$$

Where $\underset{u_{rand}}{\longrightarrow}$ denotes randomly generated position vector.

In Figure 3, some of the probable sites surrounding a solution with B>1 are shown.

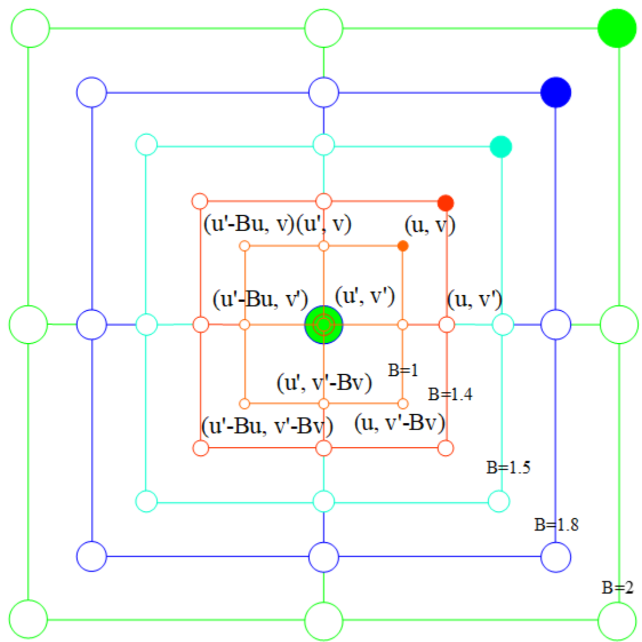

Fig 3. WOA has an exploration mechanism ('u' is a search agent chosen at random)

To make searching and attacking easier, a parameter is decreased from II to 0. When |P| > 1, a random search agent is chosen, however since $|\underset{P}{\rightarrow}| < 1$ is selected, and the good option for updating the search agents' positions is chosen. WOA may flip between spirals and a round movement depending on the value of p. Lastly when a termination condition is met, the WOA algorithm is terminated.

Because it includes exploration/exploitation capabilities, WOA may theoretically be called a global optimizer. In addition, the proposed hypercube approach establishes a search region around the best answer, allowing additional search agents to use the current better details within that region. The WOA algorithm can quickly transition between exploration and exploitation due to adaptive changes in the search vector A: by reducing P, certain iterations are given to exploration ($|P|$ 1) and the remainder to exploitation ($|P|$ 1). It's odd that WOA only has two internal settings that can be adjusted (P and Q).

Although we might have included mutations and other evolution in the WOA formulations to completely reproduce humpback whale behavior, we elected to simplify the WOA algorithm by reducing the amount of heuristics and internal parameters. On the other hand, hybridization utilizing evolutionary search techniques might be the subject of future research.

2.3 LSTM

The LSTM network is a form of RNN that combines representation learning and model training without the requirement for extra domain knowledge.

LSTM is specifically developed to address the problem of gradient vanishing, which makes it difficult to retain the short- and long-term correlation between vectors. We also looked at the influence of single parameter optimization on the proposed approach and found that only learning rate optimization had little impact on the proposed LSTM's performance. The suggested LSTM's overall performance improves when the learning rate, momentum rate, and dropout rate are all optimized together. Here, the weight of the LSTM is obtained by HHO.

2.4 Harris Hawks Optimization (HHO)

This technique appears to be a metaheuristic optimization method. It replicates Harris Hawks' co-operative "surprise pounce" behavior Exploitation and Exploration levels are present in the HHO strategy, as they are in other metaheuristic algorithms. HHO is a population-based optimization method that does not use gradients. As a result, when properly formulated, it can be used to resolve every optimization issue. In the HHO algorithm, exploration have2 stages, and exploitation have 4 stages. There are two exploration stages and four exploitation steps in the HHO algorithm. This cooperative behavior's mathematical model also presents a novel stochastic technique for tackling a number of optimization issues. In the following section, to suggest a DVR control scheme, the HHO approach is applied.

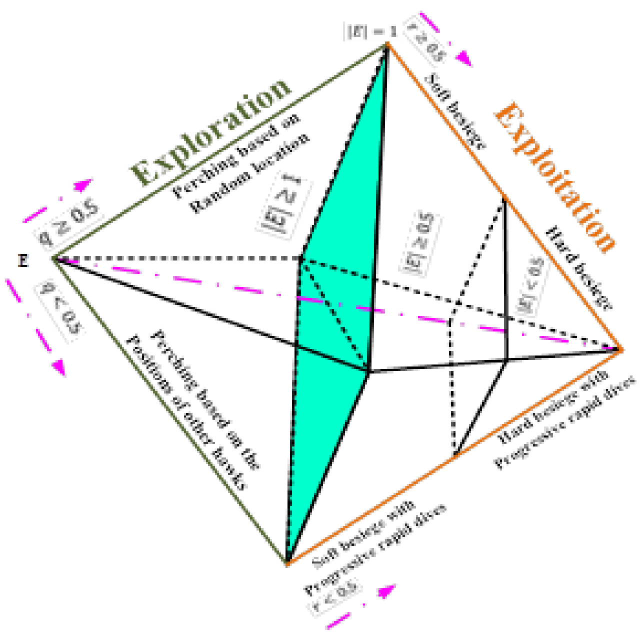

Fig 4. HHO in various phases

We simulate the proposed HHO's exploring and exploitative stages in this part, which are based on Harris hawk prey investigation, surprise pounce, as well as a variety of attack methods. HHO can solve an optimization issue with the appropriate formulation because it is a population-based, gradient-free optimization strategy. Figure 4 depicts all HHO phases, which have been described in detail in the subsequent.

2.4.1 Exploration Phase:

Throughout this stage, HHO roams around in random places, looking for prey utilizing one of two methods. To alter the location of each hawk, an equation is utilized (Equation (9)). The Ki1, Kp1, Kp2, & Ki2 PI controller parameters are the "prey" in our scenario, although the "hawks" are the variety of recommended search agents.

$$y(L+1) = \begin{Bmatrix} (y_{PREY}\,(L) - y_M\,(L)) - C_3\,(lb + C_4\,(ub - lb)), & k < 0.5 \\ y_{RAND}\,(L) - C_1\,|y_{RAND}\,(L) - 2C_2\,y(L)|, & k \geq 0.5 \end{Bmatrix} \tag{9}$$

Where:

$y\,(L+1)$ is the hawks' next iteration's location vector,

$y_{PREY}\,(T)$ is the prey's location (Kp1, Ki1, Kp2, and Ki2),

K, c1, c2, c3, c at each cycle, are the random integers inside (0,1)

$y(L)$ Hawks' current location vector is c1, c2, c3, c4,

$y_{RAND}(L)$ is a hawk chosen at random from the present population,

lb, ub The upper and bottom bounds of the variable, signifying the lowest and highest values, are denoted by Kp1, Ki1, Ki2, and Ki2.

The hawks arrive at an average location using the Equation (10),

$$y_M(L) = \frac{1}{n}\sum_{I=1}^{n} y_I(L) \tag{10}$$

where:

$y_M(L)$ hawks' average starting position,

$y_I(L)$ each hawk's location on iteration 't',

n denotes the number of hawks (n=10 here due to the multitude of search engines).

2.4.2 Exploration To Exploitation Transition:

$$e = 2e_o\left(1 - \frac{T}{t}\right) \tag{11}$$

Because the prey tries to run, the change between exploitation and discovery, and the transition from searching to attacking takes place. The victim expends a great deal of energy striving to escape. Equation (11) simulates the prey's energy equation:

where:

e denotes the prey's fleeing energy, t the maximum number of repetitions, and$e_o$the energy's beginning condition.

2.4.3 Exploitation Phase:

2.4.3.1 Soft Besiege:. Before swooping down on the victim, the HHO softly circles it to exhaust it. This action is explained by Equations (12) and (13).

$$y(L+1) = \triangle y(L) - e\left|ky_{PREY}(L) - y(L)\right| \tag{12}$$

$$\triangle y(L) = y_{PREY}(T) - y(L) \tag{13}$$

Where,

In iteration t, $\triangle y(T)$ represents the difference between the current location of hawks and prey.

K: the strength of the prey when bouncing randomly during the escape is known as k=2 (1-c5). To imitate the natural behavior of prey, this value fluctuates at random during each cycle.

R: is the escape prey possibility.

2.4.3.2 Hard Besiege:. In this situation, the victim is unable to depart due to exhaustion. As a result, hawks have an easier time catching and pinning their prey. Each hawk takes use of its existing position to improve its circumstances (Equation (14)).

$$y(T+1) = y_{PREY}(T) - e\left|\triangle y(T)\right| \tag{14}$$

2.4.3.3 Progressive Rapid Dives In a Soft Besiege. Imagine that hawks can use the following rule to analyze (decide) their next action.

$$h = y_{PREY}(L) - e\left|Ky_{PREY}(L) - y(T)\right| \tag{15}$$

The HHO technique uses the LF (Lévy Flight) principle can build the differential equation to mimic the prey's zigzag motion when attempting to elude. There under the LF principle, hawks should dive for their prey Equation (16). Equations (17) and (18) LF function.

$$g = h + s \times lf(d) \tag{16}$$

$$lf(X) = 0.01 \times \frac{U \times \propto}{|V|^{\frac{1}{\delta}}} \tag{17}$$

$$\alpha = \left(\frac{r(1+\delta) \times \sin\left(\frac{\pi\delta}{2}\right)}{r\left(\frac{1+\delta}{2}\right) \times \delta \times 2^{\left(\frac{\delta-1}{2}\right)}} \right)^{\frac{1}{\delta}} \tag{18}$$

Where, d is denoted as the problem's dimensionality is denoted a $1 \times d$ random vector, if denoted a levy flight function.

2.4.3.4 Progressive Rapid Dives In a Hard Besiege. By minimizing the distance between the average location as well as the prey location, team members' whereabouts are revealed.

$$y(L+1) = \begin{Bmatrix} h & IF\ f(h) < f(y(L)) \\ g & IF\ f(g) < f(y(L)) \end{Bmatrix} \tag{19}$$

If h and g were calculated using the additional criteria Equations (20) and (21):

$$h = y_{PREY}(t) - e\,|Ky_{PREY}(T) - y_M(T)| \tag{20}$$

$$g = h + s \times lf(d) \tag{21}$$

Where, $y_M(T)$is obtained from Equation (10).

3 Result and Discussion

The performance metrics of RMSE and MAE are acceptable. Three approaches are compared: the suggested method, the traditional LSTM, and the SVM.

Analysis of solar power in sunny day V/S time is shown in Figure 5 for the survey of solar power sunny time series 15 mints data- Austria. The LSTM and SVM in this condition are actual, hypothetical, and conventional. In comparison to other 800 MW time 10:00:00, conventional LSTM is at its peak value. Comparing actual data to other data, it is in a low range. Over 600MW is the suggested value.

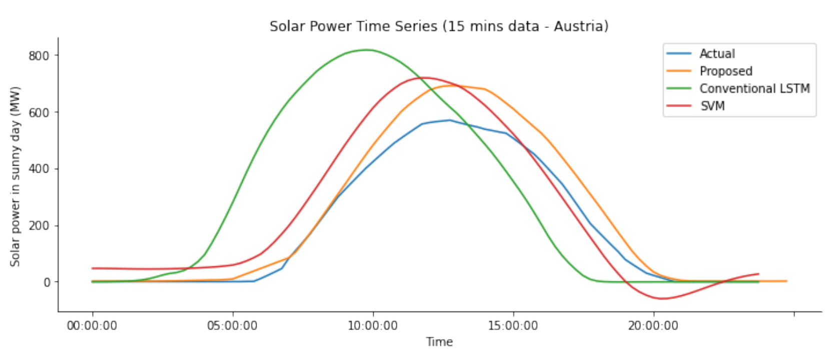

Fig 5. Solar power Sunny time series (15 mints data- Austria)

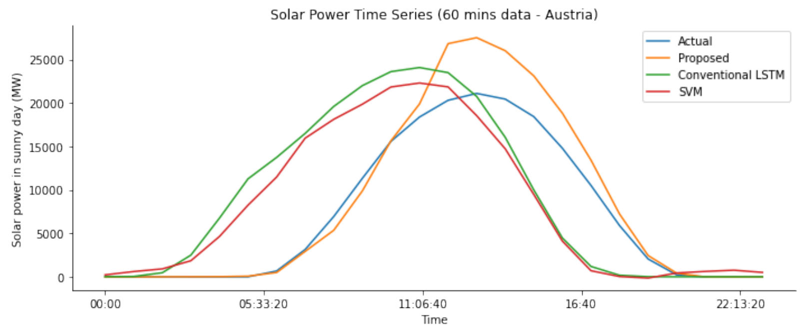

Fig 6. Solar power Sunny time series (60 mints data- Austria)

Analysis of solar power in sunny day V/S time is shown in Figure 6 for the survey of solar power sunny time series 60 mints data for Austria. Comparing actual, proposed, conventional LSTM and SVM under this condition. Proposed is the peak value when compared to others who use more than 25000 MW at 11:06:40. Actual data are in the low to mid-teens compared to other data of 20,000 MW.

Analysis of solar power in sunny day V/S time is shown in Figure 7 for the survey of solar power sunny time series 15 mints data from Germany. In this condition, the proposed, actual, conventional LSTM and SVM are compared. When compared to others, the conventional LSTM reaches its peak value at 11:06:40. Comparing actual data to other data above 20,000, it is low range. The suggested amount is 25,000 MW.

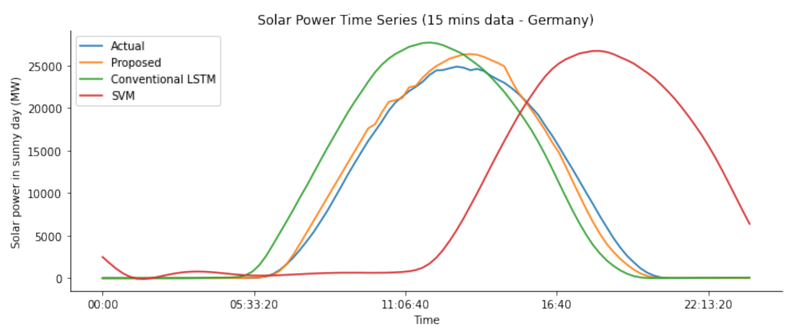

Fig 7. Solar power Sunny time series (15 mints data- Germany)

Figure 8 illustrates an analysis of solar power on a sunny day versus time for 60 minutes of data from Germany. The LSTM and SVM in this condition are actual, hypothetical, and conventional. Compared to other peaks over 30000 MW, the proposed peak value is 11:06:40. Traditional LSTM and SVM have a limited range when compared to other data above 5000MW time 05:33:20.

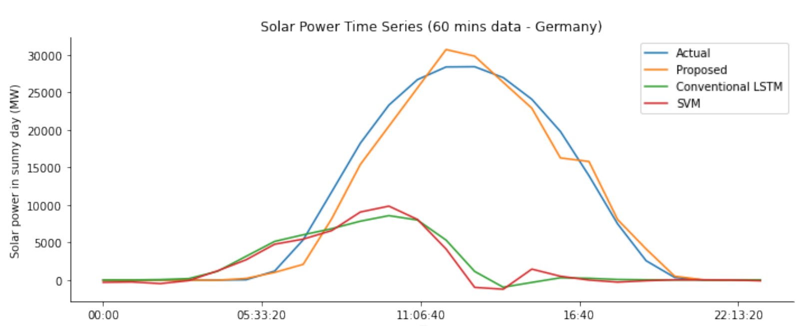

Fig 8. Solar power Sunny time series (60 mints data- Germany)

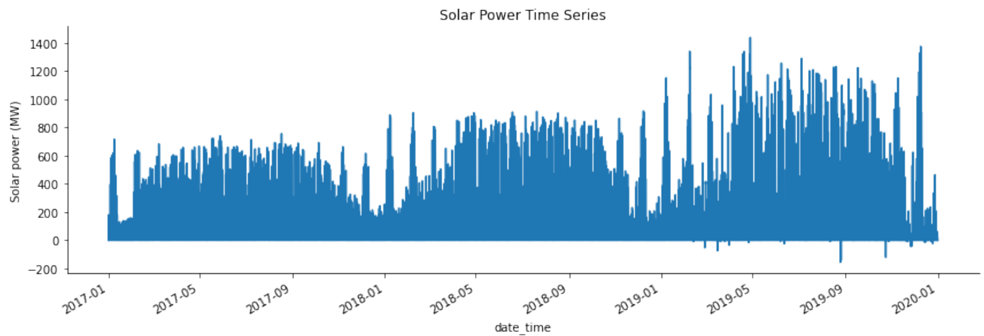

Fig 9. Solar power time series in future prediction

Figure 9 displays the analysis of solar power V/S date-time for the survey of solar power time series in future prediction. The starting solar power range for the year 2017 is 700MW, the midyear solar power range is slightly higher than 700MW, and the year-end solar power range is 800MW. The solar power range for 2018 is 800MW, with an additional 800MW for the middle and end of the year. The solar power range for the year 2019 starts above 800 MW, increases to above 1200 MW in the middle of the year, and decreases to above 1000 MW at the end of the year. Analysis of 1200MW of solar power feature predictions for 2020.

Table 1. The comparative analysis of the proposed model and the existing model

Country	Data type	Processing type	Metrics	Proposed	Conventional LSTM	SVM
Austria	**15 mins**	Training process	RMSE (MW)	3.07	15.87	259.95
			MAE (MW)	6.62	10.28	172.07
		Testing process	RMSE (MW)	3.24	15.86	262.63
			MAE (MW)	7.03	9.7	168.81
	60 mins	Training process	RMSE (MW)	5.61	19.86	259.87
			MAE (MW)	18.64	20.52	191.52
		Testing process	RMSE (MW)	5.87	17.36	260.12
			MAE (MW)	19.63	22.79	187.33
Germany	**15 mins**	Training process	RMSE (MW)	13.53	212.66	8212.8
			MAE (MW)	120.39	144.82	4892.79
		Testing process	RMSE (MW)	13.26	211.96	7403.08
			MAE (MW)	115.89	141.71	4210.66
	60 mins	Training process	RMSE (MW)	21.18	520.64	8217.02
			MAE (MW)	269.52	332.2	4833.61
		Testing process	RMSE (MW)	21.86	535.22	7356.05
			MAE (MW)	279.85	342.43	4109.6

4 Conclusion

In this study, we describe a hybrid technique for enhancing the accuracy of solar power forecasts over short periods. We used a genuine numerical solar power dataset and a conventional pre-processing method for our study. The Whale Optimization Algorithm is used to pick features in this study (WOA). The accuracy of solar power estimates is determined using an LSTM (Long Short-Term Memory) approach. The HHO (Harris Hawks Optimization) method is also employed to increase the accuracy of solar power forecasts. The findings imply that the suggested method considerably enhances the accuracy of short-term solar power estimates. Results were examined, and the recommended method was implemented in Python. Solar energy in sunny day versus time solar energy in sunny time series for 15 minutes – Austria, in this situation, the LSTM and SVM are at their highest values when compared to other 800 MW times 10:00:00. Proposed, traditional LSTM and SVM for Austrian solar power sunny time series data for 60 mints. When compared to other users who use more than 25000 MW, proposed is the peak value at 11:06:40. When compared to other data of 20,000 MW, the actual data are in the low to mid-terms. data from Austria for 15 minutes comparing solar power on cloudy days to time. To compare to others who use more than 400 MW, the suggested peak time for conventional LSTM and SVM in this situation is 16:40. The conventional LSTM reaches its maximum value at 05:33:20 for 60 minutes of Austrian data on solar power in cloudy days.

German data for a 15-min period on solar power in sunny days versus time. At 11:06:40, the conventional LSTM reaches its maximum value. Solar energy on a cloudy day Traditional LSTM and SVM are at their peak when compared to others above 12000 MW during the survey of solar power over a 60-min period in Germany. 1200MW of solar power feature predictions for 2020 are based on solar power VS date-time solar power time series. This is a lot less than bench marking errors. Future research will look at how well the suggested method predicts additional renewable energy sources, like the amount of electricity generated by wind farms.

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