

Article

A Survivor-Based Multilayer Perceptron for Short-Term PV Power Forecasting

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Abstract

Accurate short-term power forecasting is essential for enhancing the efficiency and reliability of energy systems. Nonetheless, conventional techniques for forecasting struggle to detect nonlinear patterns in power time series, as maintaining both stability and accuracy in predictions is tough. This research presents a unique prediction framework that integrates a Multilayer Perceptron (MLP) with survivor-based evolutionary selection strategies. The proposed neural network architecture comprises three hidden layers containing 32, 16, and 8 neurons, respectively. This enables the network to extract features while preserving essential information progressively. A Survivor selection process is employed to enhance the model's efficacy. This approach retains the optimal training models for subsequent training phases. This technique enhances both predictive accuracy and training efficiency. The amalgamation of Survivor-based selection methodologies with MLP architectures for short-term power generation forecasting is overlooked in the existing literature, although it holds promise. Thus, the proposed model is evaluated against established baselines, including Linear Regression (LR), Random Forest (RF), and Support Vector Regression (SVR). The results from 30 distinct trials indicate that the proposed MLP (32-16-8) combined with the Survivor approach exhibits the minimal prediction errors, with a mean absolute error (MAE) of 5.3588 and a root mean square error (RMSE) of 10.0216. This strategy is superior in minimizing errors compared to alternative methods. Furthermore, statistical analyses utilizing the Wilcoxon signed-rank test and paired t-test indicate that the proposed method significantly outperforms SVR and RF, while displaying performance comparable to LR. The findings indicate that including a Survivor-based selection mechanism in the MLP training process is an effective and reliable method for forecasting short-term generation power.



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1. Introduction

The rise in global energy consumption and environmental issues associated with fossil fuels have accelerated the swift advancement of renewable energy technology [1]. Solar energy, in conjunction with wind energy, is a prominent renewable energy source utilized for power generation. The International Energy Agency (IEA) reports that solar photovoltaic

(PV) energy constitutes two-thirds of all renewable electricity technologies [2]. According to this research, PV systems are projected to dominate electricity production, becoming essential for all nations in the forthcoming years. The growing adoption of solar energy offers an eco-friendly substitute for fossil fuels, although it introduces various issues regarding integration into current energy systems, grid stability, and energy management [3].

The variability of meteorological conditions, especially solar radiation and temperature, directly affects the amount of power generated, making it difficult for PV systems to operate stably [4]. Producers who generate electricity with PV systems are required to plan and commit to the amount of electricity they will produce the next day according to the rules of the electricity markets [5]. Accurately predicting the amount of electricity they will generate the next day in the short term is vital to avoid penalties if they fail to meet their commitments. Because power generation in PV plants is largely dependent on meteorological conditions, variables such as solar radiation, temperature, relative humidity, and cloud cover are used as input data in forecasting models [6].

Accurate short-term PV power forecasting is not only important for prediction accuracy but also for the reliable operation of modern energy systems. Forecasting errors may lead to inefficient generation scheduling, increased balancing costs, reserve allocation uncertainties, and financial penalties in electricity markets. As the penetration of renewable energy sources continues to increase, system operators require reliable short-term forecasts to support grid stability, energy trading decisions, and effective energy management. Therefore, improving forecasting performance remains a critical challenge with both technical and practical significance [3,5].

Numerous forecasting methods have been evaluated and suggested in recent years to enhance the precision of these predictive models. These methodologies are typically classified into three categories: statistical models, machine learning (ML) techniques, and deep learning (DL) methods. Among these methods, machine learning models are favored for their capacity to identify nonlinear correlations between climatic variables and PV energy output. Hybrid forecasting methodologies, integrating various algorithms or optimization strategies, have garnered considerable attention in recent years, alongside established machine learning models.

Hybrid models aim to maximize prediction accuracy by leveraging the strengths of different models while reducing the individual limitations of each [7–10]. Despite the successful results obtained by hybrid prediction models, the integration of evolutionary survival-based selection mechanisms into Multilayer Perceptron (MLP) architectures for short-term PV power prediction has received limited attention in the current literature. Therefore, this study proposes a hybrid short-term PV power prediction model integrating a multilayer sensor architecture with a survival-based evolutionary selection strategy using meteorological input variables. This approach improves prediction accuracy and convergence stability in short-term PV power prediction by ensuring the model maintains the most effective network configurations during training.

The primary findings of this research work can be expressed through these three points.

- The development of a new hybrid forecasting system that combines MLP architecture with a Survivor-based evolutionary selection method allows accurate short-term PV power predictions.
- The optimization system develops through the process of training, which maintains all successful network designs so that it delivers better performance and protection against errors.
- The proposed MLP (32-16-8) + Survivor method achieves better error reduction together with stable forecasting results according to the comprehensive evaluation against standard baseline models.

The authors found that research studies that explored the application of Survivor-based evolutionary selection methods to MLP systems for predicting PV power generation remain limited.

2. Related Works

Early studies on predicting how much power PV systems are going to generate employed physical models that included meteorological data such as solar radiation and temperature, with information about the panels, in order to do math on how PV conversion processes worked. The models are easy to understand because they are based on physical principles, but they cannot make effective predictions when the weather is very changeable or unpredictable [11,12].

Data-driven methodologies have undergone swift advancement, leading to a heightened application of ML techniques for PV power forecasting. Artificial neural networks, support vector regression (SVR), random forests (RF), and gradient boosting algorithms exhibit a proficient ability to estimate nonlinear relationships between meteorological inputs and PV generation [13]. DL techniques have gained prominence due to their capacity for automatic identification of complex spatial and temporal patterns within extensive datasets [14]. Researchers have analyzed various architectural designs, including CNN, recurrent neural networks (RNN), long short-term memory (LSTM), and transformer-based models, to assess their efficacy in enhancing forecasting performance [15–17].

The research field has developed a new direction of study through the creation of hybrid forecasting models, which combine multiple forecasting methods into a single unified system. Hybrid approaches use different methods together with their complementary strengths to achieve better robust performance and better prediction results during various weather conditions [7,18].

Asiedu et al. compared single and stacked hybrid models that used RF, XGBoost, and Artificial Neural Networks (ANN) over different time periods. The research assessed the efficacy of the models individually throughout one-day, one-week, two-week, and one-month forecasting intervals. The results showed that the hybrid RF-XGBoost model performed a better job of predicting PV power for one week [19]. Bai et al. developed the HWGC-WPD-LSTM hybrid model by combining Wavelet Packet Decomposition (WPD) and LSTM networks. They used real data from a power plant in Shandong. The model exhibited significant accuracy and stability in short-term PV energy forecasting, as indicated by the findings [20]. Xiang et al. created a way to predict solar output that uses a TCN-XGBoost model and dynamic meteorological correlation analysis. The research discerned the predominant climatic variables influencing PV production and incorporated these correlations into the model's loss function to enhance predictive precision.

The proposed method demonstrated excellent forecasting results through its R^2 values of more than 0.95 and lower Root Mean Square Error (RMSE) compared to traditional forecasting models [21]. Wu et al. proposed a complete ensemble empirical mode decomposition with adaptive noises (CEEMDAN)-convolutional neural networks (CNN)-gated recurrent unit (GRU) hybrid model for short-term PV power forecasting. Results showed that the proposed model achieved higher accuracy and lower RMSE and MAPE compared with LSTM, GRU, and other hybrid models [22]. Zhou et al. proposed an Attention-DCC-BiLSTM-AR (ADBA) hybrid model for ultra-short-term PV power forecasting that combines attention-based feature weighting with parallel linear and nonlinear prediction components. The model uses AR to model linear patterns and DCC-BiLSTM to extract nonlinear spatiotemporal features, which enables it to achieve better prediction accuracy and reliability than CNN, DCC, and LSTM-based and AR benchmark models [23].

At the same time, recent research shows another important trend: using optimization algorithms based on nature, especially animal behavior, to improve prediction models by using model integration techniques. These techniques let users fine-tune model parameters, choose input features, and change network architectures, which helps them obtain greater prediction accuracy and faster convergence outcomes. Simultaneously, decomposition methods that break down complicated and non-stationary PV energy dynamics into smaller parts have been extremely common in the literature on PV energy forecasting. These dynamics are hard to show with just one model. One example is a hybrid model that uses Variational Mode Decomposition (VMD), Whale Optimization Algorithm (WOA), and LSTM neural networks to make PV power predictions more accurate by optimizing model parameters [8]. The study that improved the Extreme Learning Machine (ELM) with the Beluga Whale Optimization algorithm (EIBWO) discovered that it had a strong fit to the solar power generation data [24] and an R^2 value greater than 0.99. Another example is a hybrid machine learning model that combines Gaussian Process Regression and Wavelet Packet Decomposition at the same time. This model achieved superior accuracy with an RMSE of 2.116% and an RMSE of 208.233 kW, surpassing many existing techniques [25]. In another study, the RF method was employed for PV power forecasting, where feature selection and optimization techniques were applied to exclude irrelevant data and enhance prediction accuracy. To improve input features, Symplectic Geometry Mode Decomposition (SGMD) was utilized, and a Bidirectional Long Short-Term Memory (BiLSTM) model was adopted in the forecasting process. The proposed hybrid model was shown to be scalable, robust, and highly applicable across different climatic conditions and PV technologies [26]. Zhu et al. conducted a research study that examined PV power forecasting through machine learning and hybrid modeling techniques. The research team used optimization methods, which included Particle Swarm Optimization (PSO), Fruit-fly Optimization Algorithm (FOA), and Satin Bowerbird Optimizer (SBO), to enhance their comparison between AdaBoost and HGBBoost algorithms. The results demonstrated that the hybrid HGBBoost–SBO model performed best because it achieved extremely accurate predictions with R^2 values approaching 0.99 and produced fewer errors than all other models [27]. Souhe et al. proposed a hybrid PV power forecasting model combining GRU and SVM, where the Ant Colony Optimization (ACO) algorithm was used to optimize the fusion weights between the models. Experimental results showed that the proposed SVM-GRU-ACO model achieved very high accuracy ($R = 0.9986$) and lower error values compared with conventional and hybrid models in the literature [28]. Similar to Whale Optimization, optimizations inspired by nature, such as Zebra [29], Chimpanzee [30], and Gray Wolf [31], have also been used in PV power forecasting.

The Survivor Algorithm functions as the study's primary research method, which uses a nature-inspired metaheuristic algorithm that derives from human competitive behavior in survival-based reality competitions instead of animal herd behavior. The algorithm develops a search method that uses team-based competition, elimination systems, and reward methods to achieve a balance between its exploration and exploitation activities. The method develops population diversity through simulations of competitor-rival interactions, which enable better optimization pathfinding in difficult problems [32].

Unlike many optimization approaches that have been used before for PV forecasting, for example, PSO, GWO, WOA, Zebra, and Chimp-based optimizers (mostly inspired by swarm intelligence and animal searching/foraging behavior), the Survivor Optimizer leans into a kind of competition-driven evolutionary selection. It keeps the better candidates, and then it gets rid of the weaker ones using a survival-style contest. Because of that, the method tends to support population diversity and also helps to lower the chance of getting stuck too early, especially when neural network tuning is happening. To the best of

our knowledge, there has been no prior work in which the Survivor Optimizer is paired with an MLP architecture for PV power forecasting, or at least not in a way that has been clearly investigated.

3. Materials and Methods

This section describes the materials, data sources, and methodological framework employed in this study. First, the PV power generation dataset and the associated pre-processing procedures are presented. Subsequently, the proposed Survivor-enhanced MLP forecasting framework, model configuration, optimization strategy, and experimental setup are described in detail. Finally, the evaluation metrics used to assess forecasting performance are introduced.

3.1. Data Description

The active power data in this study were obtained from a PV power plant with an installed capacity of 110 kWe (129.6 kWp) located in Zonguldak, Türkiye. The plant is situated at 41°25′35.004″ North latitude and 32°4′32.016″ East longitude. The power plant uses monocrystalline photovoltaic panels, each with a power output of 400 Wp. The electrical characteristics of the panels used are given in Table 1. Data obtained from the plant’s monitoring system recorded active power measurements every 15 min between 4 January 2021, and 5 January 2025. In addition to the active power data of the PV panels, the dataset also includes temperature-2 m (°C, T), relative humidity-2 m (% RH), wind speed-10 m (km/h, WS), direct radiation (W/m², DR), direct normal radiation (W/m², DNI), perceived temperature (°C, AT), terrestrial radiation (W/m², TR), wind direction-100 m (°, WD), dew point-2 m (°C, DP), and cloud cover (% CC) obtained from the open-meteo [33] for the same date ranges and period for the region where the panels are located.

Table 1. PV panel electrical characteristics.

Label Values	Unit
Peak Power (Pmax)	400 Wp
Module Efficiency (%)	20.06
Maximum Power Voltage (Vmp)	41.10 V
Maximum Power Current (Imp)	9.75 A
Open Circuit Voltage (Voc)	49.83 V
Short Circuit Current (Isc)	10.38 A
Power Tolerance	0 ~ +5 W
Operating Temperature	−40 ~ +85 °C

For the forecasting models, the input feature set consisted of the meteorological variables (temperature, relative humidity, wind speed, direct radiation, direct normal radiation, apparent temperature, terrestrial radiation, wind direction, dew point, and cloud cover) together with the active power value from the previous time step ($t - 1$). The target variable was the active power output at the current time step (t). Accordingly, the forecasting task was formulated as a one-step-ahead PV power prediction problem with a forecasting horizon of 15 min.

Prior to model training, the dataset was inspected for missing and invalid observations, which were removed when detected. To formulate the forecasting problem, a lagged feature was generated by using the active power value at the previous time step ($t - 1$) as an input variable, while the active power value at the current time step (t) was used as the prediction target. All input variables were normalized to the range [0, 1] using the MinMaxScaler technique to improve training stability and convergence. Finally, the dataset was divided

into training (80%) and testing (20%) subsets without shuffling in order to preserve the temporal structure of the time-series data.

3.2. Survivor Algorithm

A novel metaheuristic optimization method derived on the principle of “survival of the fittest.” The algorithm sustains a population of candidate solutions that fight for dominance, with worse answers being progressively discarded while superior solutions facilitate the development of subsequent iterations. This competitive selection mechanism enables the algorithm to balance the investigation of new areas in the search space with the exploitation of promising locations, thus ensuring both efficiency and robustness in the optimization process. By preserving diversity within the population, the technique circumvents premature convergence to local optima, a frequent drawback of conventional metaheuristics.

The general framework of the proposed Survivor Optimizer (SO) is shown in Figure 1. The optimization process begins with the initialization of the population and the separation of candidate solutions into two competitive groups. All persons are rated for fitness, and the best candidate in each group is determined. The algorithm is based on this competitive structure. It enables individuals to interact and exchange information about their performance, instead of just relying on conventional population updates.

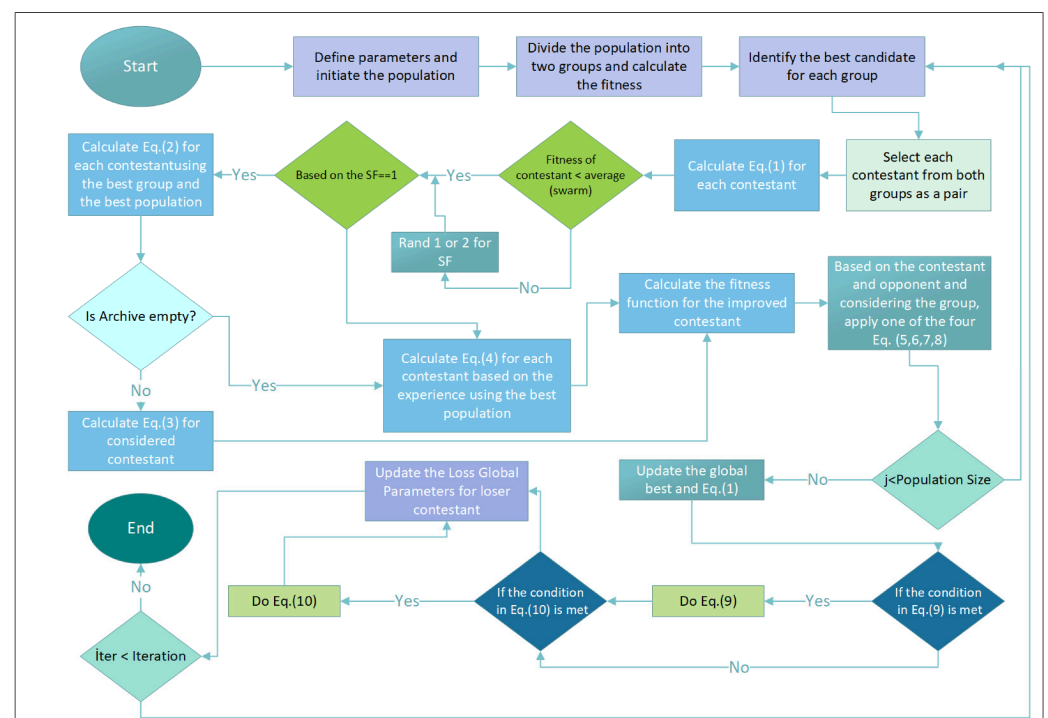


Figure 1. Flowchart of Survivor Metaheuristic Optimization [32].

Following the grouping stage, contestants from both groups are paired and evaluated through a competition mechanism. During this process, stronger candidates influence the search behavior of weaker contestants, encouraging the population to move toward promising regions of the search space. As opposed to many traditional population-based optimizers that use the same search rules to update all individuals, SO introduces a competitive learning strategy in which search decisions are driven by both local group leaders and global knowledge of the population. This mechanism aims to improve information sharing while reducing the risk of premature convergence.

Another important component of the algorithm is the integration of archive-guided learning. Previously discovered high-quality solutions are stored and later reused to

guide the search process. By exploiting historical search experience, the algorithm can revisit promising regions that might otherwise be lost during stochastic updates. This archive mechanism contributes to maintaining population diversity and improving search continuity throughout the optimization process.

The workflow includes adaptive update and refinement steps. Depending on the optimization state, candidate solutions may be subjected to exploitation-oriented movements toward high-quality solutions or exploration-oriented modifications to foster the exploration of unexplored regions of the search space. Moreover, the algorithm dynamically adjusts its search behavior in different optimization stages by constantly updating the parameters associated with the winning and losing individuals.

The final stages of the algorithm focus on updating the global best solution and refining the search process through adaptive control mechanisms. These operations help balance exploration and exploitation while preventing excessive concentration around local optima. The iterative procedure continues until the stopping criterion is satisfied, after which the best solution discovered during the optimization process is returned.

For clarity, the mathematical formulations corresponding to each optimization stage, including the candidate updating, archive search, winner–loser adaptation, exploration reset and parameter control mechanisms, are summarized in Table 2. The combination of competitive interactions, archive-guided learning, and adaptive refinement allows SO to maintain population diversity and efficiently converge to high-quality solutions.

Table 2. Formulas of Survivor.

No.	Process Stage	Description
1	Impact Factor Update	$F_i = F_i + 0.1 \times (\text{rand}[0,1] - F_i)$ Updates impact factor F_i representing energy decay
2	Exploitation Movement	$Ct_i = Ct_i + \text{rand}[0,1] \times (GB - Ct_i) \times (GRB_k - Ct_i)$ Uses Global Best (GB) and Group Best (GRB_k) for exploitation
3	Archive Search	$Ct_i = Ct_i + F_i \times (Ct_i - \text{Ar}(\text{rand_idx}))$ Exploration using archived best solutions (Ar)
4	Force & Position Update	$Ct_i = Ct_i + [W \times Ct_F + Ct_W \times \text{rand} \times ((GB + GRB_k)/\sqrt{F_i \times Ct_{ML}} - Ct_i)]$ Balances exploration and exploitation via weight W
5	Group 1 Loss Update	$Ct_{L1} = 0.5 \times \sqrt{(Ct_{L1} + Ct_{W1})/\text{iter}}$ Updates loss energy of Group 1 losers
6	Group 2 Loss Update	$Ct_{L2} = 0.5 \times \sqrt{(Ct_{L2} + Ct_{W2})/\text{iter}}$ Updates loss energy of Group 2 losers
7	Group 1 Win Update	$Ct_{W1} = 0.5 \times \sqrt{(Ct_{L2} + \text{iter}) + Ct_{CL1}}$ Updates winner energy of Group 1
8	Group 2 Win Update	$Ct_{W2} = 0.5 \times \sqrt{(Ct_{L1} + \text{iter}) + Ct_{CL2}}$ Updates winner energy of Group 2
9	Exploration Reset G1	$Ct_k = F_i \times GB$ Reinitializes loser using global best guidance
10	Exploration Reset G2	$Ct_k = F_i \times GB$ Reinitializes loser in Group 2
11	Regularization	$Ct_{LL} = Ct_L \times Ct_{LD}$ Prevents over-exploitation and stabilizes search
12	Weight Damping	$W = W \times WD$ Reduces search intensity over iterations

Conceptual Analysis of the Survivor Optimization Process:

Table 2 is structured based on the workflow illustrated in Figure 1, where each of the ten formulas provides a detailed description of the operations defined within the corresponding blocks of the flowchart to guide the weight optimization process. It summarizes the mathematical foundations of the SO algorithm across four primary operational phases, designed specifically for the intelligent optimization of MLP weights:

- **Energy Management Phase (Formula (1)):** The algorithm controls the dynamic movement and step-size of each potential solution (contestant) using the Impact Factor concept. This formula ensures that each agent moves through the search space with an energy level proportionate to its current state and survival potential.
- **Exploitation and Convergence Phase (Formulas (2), (4), (7) and (8)):** In this stage, the algorithm leverages the best experiences found by the entire population (Global Best) and successful sub-groups. The formulas associated with Winners increase the energy and score of high-performing solutions, allowing the neural network to converge toward the minimum error rate with greater speed and precision.
- **Exploration and Escape Phase (Formulas (3), (9) and (10)):** This section is the primary differentiator of this algorithm. The More Loser mechanism intelligently identifies sets of weights trapped in “local optima.” By executing these formulas, weak solutions are eliminated and reinitialized with fresh energy in unexplored regions of the search space, ensuring that the opportunity to discover superior global solutions is maintained.
- **Competition and Archive Learning Phase (Formulas (5) and (6)):** By simulating a competitive environment, the algorithm continuously evaluates the quality of solutions based on their error metrics. During this phase, the energy of underperformers is reduced, and the use of an Archive (a library of historical bests) allows the model to learn from successful paths taken in the past, preventing the repetition of previous errors.

Figure 2 depicts a machine learning framework that starts with Data Sets and Feature Selection, moves forward to Data Preprocessing (encompassing scaling and encoding), and subsequently employs the SO to optimize the hyperparameters of MLP to produce final Predictions.

Because these models function fundamentally differently, the MLP is the main target of the SO Algorithm. Both SVR and Linear Regression (LR) are regarded as deterministic or theoretically simple; SVR involves complicated quadratic programming that would become computationally exhaustive if optimized by an evolutionary algorithm, while LR has a closed-form mathematical solution that does not require metaheuristic searching. An MLP, on the other hand, has a very non-convex loss landscape that is full of “traps” or local optima. The network can escape local minima and converge toward a better global solution because of the SO algorithm’s special mechanisms, such as the Impact Factor and More Loser strategies, which are specifically made to negotiate these intricate weight spaces.

The other models, LR, SVR, and RF, are also used as baseline models in this research strategy. By keeping these algorithms in their normal or standard settings, it is easy to see how much “added value” the SO integration brings. This method shows that the MLP + Survivor combination’s better performance is not just a coincidence; it is a direct effect of the optimization process. It shows how new the algorithm is by showing that it can do better than typical machine learning approaches that do not include a weight-tuning mechanism that changes with time.

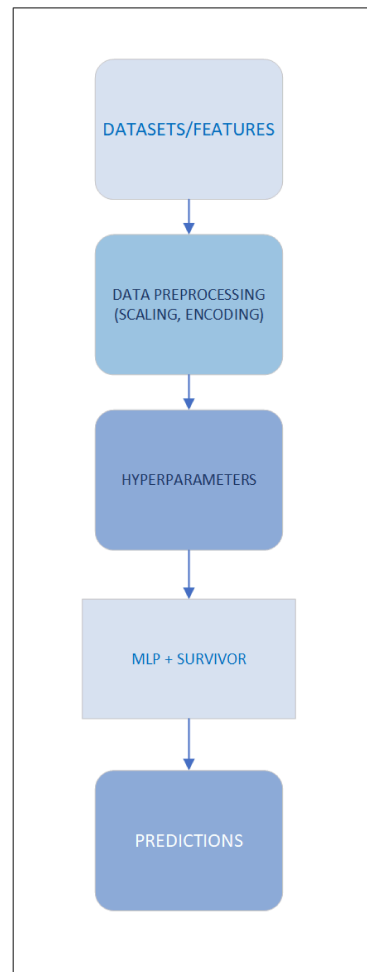


Figure 2. Flowchart of General Method.

4. Experimental Analysis

The experimental results reported in the original Survivor Optimizer (SO) study demonstrated that the algorithm outperformed several traditional optimization methods on both benchmark functions and real-world optimization problems. The proposed approach achieved higher solution quality, faster convergence, and improved stability, indicating its effectiveness in solving complex nonlinear optimization tasks. Furthermore, its adaptive and competitive search mechanism makes it particularly suitable for applications where maintaining population diversity and achieving a proper balance between exploration and exploitation are critical for obtaining high-quality solutions [32].

The dataset was split into training and testing subsets using an 80–20% hold-out approach for model development. The training was performed on the first 80% of the observations, and testing was performed on the remaining 20%. As the study involves a time-series forecasting problem, the data were kept in order without shuffling to preserve the time order of the observations. The training subset was used for model learning and survivor-based optimization, and the testing subset was used exclusively for performance evaluation. All reported MAE, RMSE, and R2 values were calculated on the unseen test set. The experimental procedure was replicated over 30 independent runs to evaluate the robustness and stability of the forecasting models.

The network architecture with three hidden layers (32-16-8 neurons) was selected based on a progressive feature compression strategy and preliminary empirical evaluations. This configuration was designed to gradually reduce the dimensionality of the learned feature representations while preserving sufficient model capacity to capture the nonlinear

characteristics of PV power generation data. The adopted architecture provides a balance between predictive performance and model complexity, avoiding unnecessary network expansion while maintaining effective learning capability.

Table 3 summarizes the operational parameters and settings utilized throughout this study, covering data preprocessing details and baseline model configurations. Specifically, it highlights the structural parameters of the MLP and the Survivor algorithm settings, such as population size and generations, to ensure the precision and reproducibility of the experimental results. To facilitate reproducibility, implementation details, parameter settings, and source code for the proposed Survivor-based MLP framework are provided at <https://github.com/vedatesen/Survivor-Short-Term-PV-Forecasting>.

Table 3. Parameters of experience.

Algorithm/Model	Parameter	Value/Setting
Common Preprocessing	Lagged Features	$t - 1$ (time steps as inputs)
Common Preprocessing	Scaling	MinMaxScaler (0–1 normalization)
Common Preprocessing	Test Size	0.2 (20% hold-out)
Common Preprocessing	Shuffle	False (time-series order preserved)
LR	fit_intercept	True
LR	normalize	False
RF	n_estimators	100
RF	random_state	1–30 (run-dependent seed)
SVR	kernel	RBF
SVR	C	1.0
SVR	epsilon	0.1
MLP	architecture	(32, 16, 8)
MLP	activation	ReLU
MLP	population size	100
MLP	generations	50
MLP	mutation std	0.05
MLP	optimizer	Survivor

For the proposed forecasting framework, the MLP architecture consisted of three hidden layers with 32, 16, and 8 neurons, respectively, using the ReLU activation function. The Survivor optimizer was configured with a population size of 100, 50 generations, and a mutation standard deviation of 0.05. For the baseline models, Random Forest employed 100 trees, while SVR used an RBF kernel with $C = 1.0$ and $\epsilon = 0.1$. These parameter settings were maintained throughout all experiments to ensure a fair and consistent comparison.

Table 4 the minimum and maximum values of each performance metric obtained across 30 independent runs for each algorithm. These values represent the best-case performance of the models. The results clearly indicate that the MLP (32-16-8) + Survivor model achieves the best predictive performance among all compared algorithms.

Table 4. Best prediction over 30 independent runs.

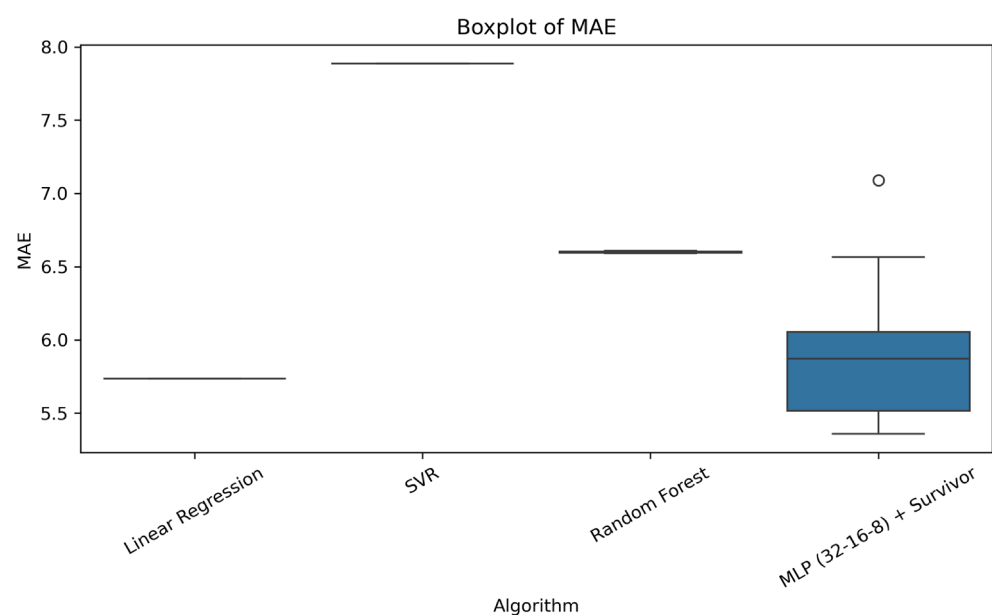
Algorithm	MAE (Min)	RMSE (Min)	R ² (MAX)
MLP (32-16-8) + Survivor	5.358836	10.021579	0.862076
LR	5.734631	10.169426	0.857977
RF	6.590857	11.294119	0.824825
SVR	7.886965	11.023509	0.833119

The proposed model has the lowest Mean Absolute Error (MAE) (5.3588) and RMSE (10.0216) based on the minimum values from 30 independent runs. This shows that it is better at reducing both absolute and squared prediction errors.

The constantly decreasing error-based measurement results show that adding the Survivor strategy to the MLP design makes the prediction mechanism work better and more efficiently. These results show that the suggested method is the most accurate model for short-term forecasting tasks when everything goes right.

This study used a one-step-ahead forecasting technique, with the input feature reflecting the power value at the preceding time step ($t - 1$) and the target indicating the power at the present time step (t). This formulation allows the models to understand how the time series data changes over short periods of time. Given that the measurements were collected at 15 min intervals, the forecasting horizon in this study corresponds to 15 min ahead.

The comparative performance of the algorithms is further illustrated through the boxplot visualizations of MAE, RMSE, and R², shown in Figures 3–5. As depicted in these figures, the proposed MLP (32-16-8) + Survivor model demonstrates a well-controlled dispersion of results across the 30 independent runs. In particular, the interquartile ranges of the boxplots are relatively compact, and the median values remain stable, indicating consistent convergence behavior throughout repeated executions. This behavior suggests that the model maintains a favorable balance between exploration and refinement during the optimization process, contributing to reliable forecasting performance.

**Figure 3.** Boxplot of the MAE metric for each algorithm.

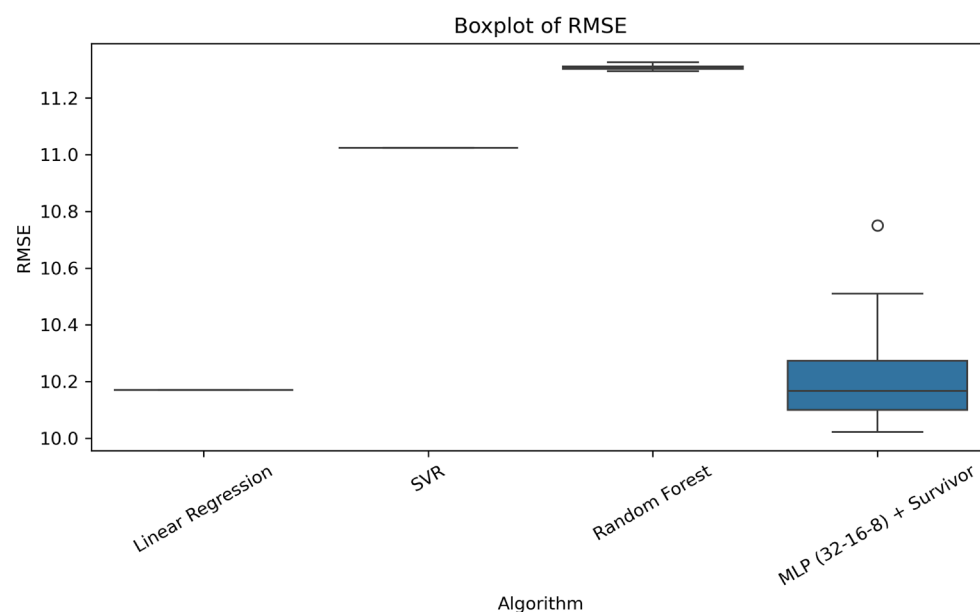


Figure 4. Boxplot of the RMSE metric for each algorithm.

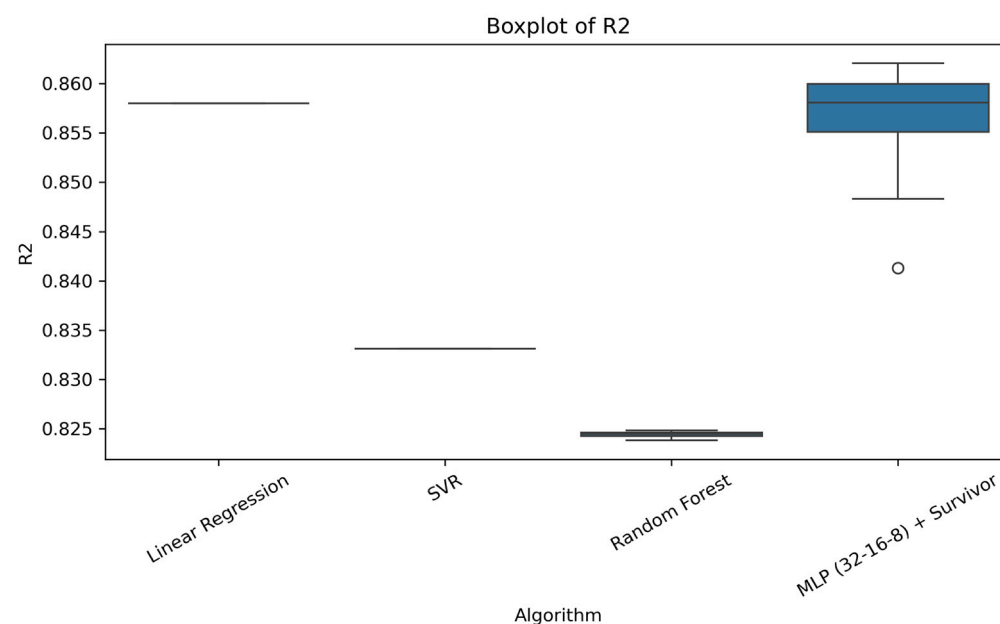


Figure 5. Boxplot of the R^2 metric for each algorithm.

The actual-versus-predicted Figures 4–6 further demonstrates the ability of the proposed model to follow the temporal evolution of PV power generation. The model successfully captures the overall production profile and maintains close agreement with the measured power values throughout the forecasting horizon. Although some deviations are observed during periods of rapid power variation, which may be associated with changing meteorological conditions, the proposed framework generally preserves the temporal dynamics of the PV generation process.

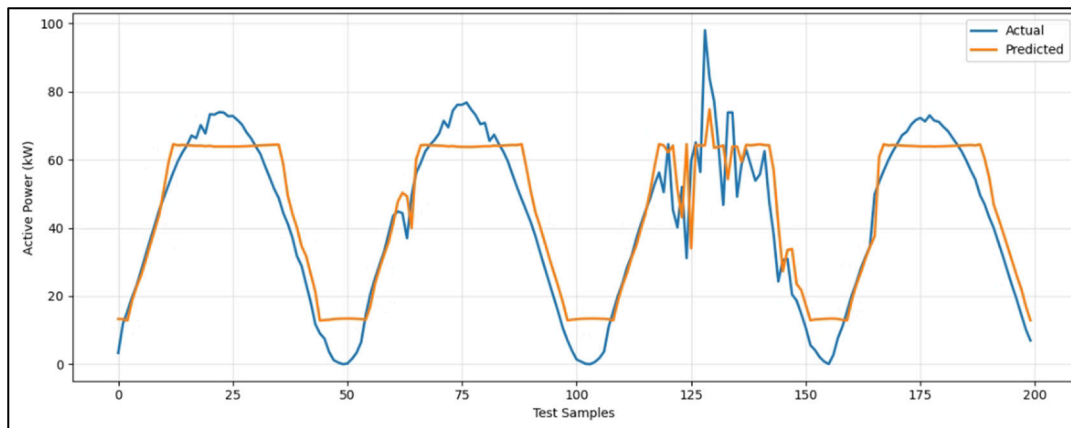


Figure 6. Actual versus predicted active power values on the test set.

In contrast, LR and SVR exhibit nearly degenerate boxplots with zero standard deviation across all three evaluation metrics, as also reported in Table 4. This phenomenon indicates that these algorithms converge to identical solutions across repeated runs, reflecting their deterministic optimization nature. Although this results in highly compact boxplots, it primarily reflects the consistency of their optimization procedures rather than variability in the learning process. RF, while exhibiting non-zero dispersion, presents slightly wider interquartile ranges than the deterministic models but remains relatively constrained due to its ensemble structure.

The combined analysis of Table 5 and Figures 3–5 highlights an important characteristic of the proposed method. The MLP (32-16-8) + Survivor framework employs an evolutionary selection mechanism that introduces controlled variability while maintaining stable central performance patterns across repeated runs. This behavior differs from fixed deterministic learning schemes and contributes to competitive predictive performance, low minimum error values, and reliable convergence characteristics. These findings suggest that the proposed method represents a promising and reliable approach for short-term PV power forecasting.

Table 5. Mean and standard deviation of MAE, RMSE, and R2 obtained over 30 independent runs.

Algorithm	MAE_Mean	MAE_Std	RMSE_Mean	RMSE_Std	R2_Mean	R2_Std
LR	5.7346	0	10.169	0	0.8579	0
MLP (32-16-8) + Survivor	5.8609	0.3752	10.2136	0.1558	0.8567	0.0044
RF	6.5990	0.0048	11.3060	0.0080	0.8244	0.0002
SVR	7.8869	0	11.0235	0	0.8331	0

Figure 6 presents the comparison of actual and predicted active power values obtained by the proposed MLP-Survivor model for a representative test period. As can be seen, the predicted values are in good agreement with the overall trend and the temporal behavior of the measured power output. The model captures the main generation patterns and most of the short-term fluctuations while small deviations are mostly in periods with rapid power variation.

To assess the statistical significance of the performance differences between the proposed MLP (32-16-8) + Survivor model and the competing algorithms, both the Wilcoxon signed-rank test and the paired t-test were conducted on the MAE, RMSE, and R^2 metrics. The results indicate that, when compared with SVR and RF, the obtained p -values are far

below the 0.05 significance level across all evaluation metrics, demonstrating statistically significant superiority of the proposed model (Table 6).

Table 6. Statistical comparison of the proposed model with baseline methods.

Metric	Compare_With	Wilcoxon_p	Ttest_p
MAE	LR	0.129353076	0.075381666
RMSE	LR	0.31839608	0.131213571
R ²	LR	0.31839608	0.126816122
MAE	SVR	1.86265×10^{-9}	3.2872×10^{-23}
RMSE	SVR	1.86265×10^{-9}	9.65796×10^{-23}
R ²	SVR	1.86265×10^{-9}	4.66895×10^{-23}
MAE	RF	1.86265×10^{-8}	1.18516×10^{-11}
RMSE	RF	1.86265×10^{-9}	2.97602×10^{-26}
R ²	RF	1.86265×10^{-9}	1.00443×10^{-26}

On the other hand, the performance differences between the proposed approach and LR are not statistically significant. This is because LR is deterministic, which means that it always gives the same output, so there is no variance. Overall, these statistical results show that the proposed model's performance is more flexible than that of other learning models and is statistically significant and not just random changes.

This study investigated one-step-ahead power forecasting using multiple machine learning models, with particular emphasis on the proposed MLP (32-16-8) + Survivor approach. The experimental evaluation, conducted over 30 independent runs, demonstrated that the proposed model consistently achieves strong predictive performance across all considered metrics. Compared to classical linear and nonlinear baseline methods, the proposed approach exhibits competitive average accuracy while maintaining controlled variability, indicating a reliable learning and optimization process. The statistical analysis further reinforces these findings. While no statistically significant difference was observed between the proposed model and LR, attributable to the deterministic nature and zero variance of the linear model, the proposed approach significantly outperforms SVR and RF according to both Wilcoxon signed-rank and paired t-tests. These results confirm that the observed improvements are statistically meaningful and not caused by random fluctuations across runs. In addition, the boxplot analyses of MAE, RMSE, and R² provide valuable insights into the distributional behavior of the models. The proposed MLP (32-16-8) + Survivor model demonstrates stable median performance and controlled dispersion across repeated runs, reflecting consistent convergence behavior. Taken together, the empirical, statistical, and visual analyses indicate that the proposed approach is particularly effective in capturing complex and nonlinear characteristics inherent in the forecasting process. Overall, the results confirm that the integration of the Survivor strategy within the MLP architecture provides a robust and competitive solution for short-term power forecasting tasks.

Computational Platform and Implementation Details

All experiments were conducted using Python 3.11 on a Windows 11 platform. The computational environment was equipped with an Intel Core i7 processor and 32 GB RAM. The same hardware and software configuration was employed for all experiments to ensure a fair and consistent comparison among the evaluated forecasting models.

The proposed framework was implemented in Python using standard scientific computing libraries. Numerical computations and data manipulation were performed with

NumPy and Pandas, while data preprocessing and machine learning models were implemented using Scikit-learn. The MLP architecture was developed using the MLPRegressor class, and the Survivor optimization mechanism was custom-implemented and integrated into the training process to optimize the network weights through survivor-based evolutionary selection. Data visualization and performance analysis were carried out using Matplotlib version 3.10.0. To facilitate reproducibility, the complete source code and implementation details have been made publicly available through the accompanying GitHub repository.

5. Results and Discussion

The experimental results indicate that the proposed MLP (32-16-8) + Survivor model provides a competitive and reliable solution for short-term PV power forecasting. As shown in Tables 3 and 4, the proposed MLP (32-16-8) + Survivor model demonstrated competitive predictive performance, achieving the lowest minimum MAE and RMSE values while maintaining stable results across repeated runs. The minimum MAE is 5.3588 and the minimum RMSE is 10.0216 over 30 independent runs. These findings suggest that the Survivor-based evolutionary selection mechanism can enhance the forecasting capability of the MLP architecture, particularly in terms of achieving low-error prediction results.

One notable trait of the proposed model is that it has stable performance across repeated runs, which is quite interesting. The boxplot analyses shown in Figures 3–5 reveal a relatively controlled dispersion of results and stable median values across multiple experimental runs, indicating that the proposed method maintains a consistent level of performance. The Survivor-based selection mechanism adds some randomness into the optimization routine, but at the same time, it still keeps convergence stability. That is different from the deterministic models like LR, since those tend to land on identical outcomes across runs because their optimization steps are fixed, and they basically do not change.

From a statistical perspective, the comparative performance of the proposed model is further supported by the Wilcoxon signed-rank and paired t-test results. The obtained *p*-values indicate that the proposed method significantly outperforms SVR and RF across all evaluation metrics, while exhibiting performance comparable to LR. These findings suggest that the proposed approach provides competitive forecasting performance and that its improvements over SVR and RF are statistically significant rather than the result of random variation.

A significant contribution of this study is the incorporation of the SO into the MLP training process, an area that has not been previously investigated in PV power forecasting. The Survivor algorithm is different from traditional optimization or metaheuristic methods that are based on animal behavior. Instead, it uses a competition-based evolutionary mechanism to keep optimal network arrangements and get rid of the worst ones. This mechanism improves the balance between exploration and exploitation, which leads to better generalization and prevents premature convergence.

From the perspective of renewable energy systems, the proposed model provides practical and impactful benefits. Accurate short-term PV forecasting is essential for grid stability, energy trading, and efficient energy management. By providing competitive forecasting accuracy and reliable predictive performance, the proposed approach may contribute to:

- More accurate short-term forecasting generation commitments;
- Reduced imbalance penalties in electricity markets;
- Enhanced integration of solar energy into smart grids.

Therefore, beyond its methodological contribution, the proposed model has the potential to support the operational efficiency and sustainability of renewable energy systems.

6. Conclusions

This research introduces an innovative hybrid forecasting framework that integrates an MLP architecture with a Survivor-based evolutionary optimization technique for short-term solar power prediction. The experimental results demonstrate that the proposed model achieves competitive forecasting accuracy and stable convergence characteristics. Furthermore, statistically significant improvements were observed compared with SVR and RF, while performance remained comparable to that of LR.

A key contribution of this study is the integration of the Survivor optimization process into PV power forecasting, extending the range of metaheuristic approaches explored for this application. The model effectively keeps high-quality solutions and improves the overall training dynamics of neural networks by adding a selection strategy based on competition to the learning process. This contributes to a forecasting framework capable of addressing the nonlinear characteristics commonly observed in PV power generation data.

This study introduces a Survivor-enhanced MLP framework that leverages competition-based evolutionary selection for PV power forecasting and demonstrates competitive forecasting performance with statistically significant improvements over SVR and RF. Beyond its methodological contribution, the proposed approach may support renewable energy applications that benefit from reliable short-term PV power forecasting, including grid operation and energy management tasks. These results suggest that the proposed model represents a promising approach for advancing data-driven solar energy integration.

Future work may focus on extending the proposed framework to multi-step forecasting, integrating additional meteorological and satellite data, and exploring its applicability to other renewable energy sources such as wind power. Future studies may also evaluate the proposed Survivor-enhanced framework against advanced deep learning architectures, including LSTM-, GRU-, and Transformer-based forecasting models.

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