

Novel Forecasting for Photovoltaic Installation Output Using Transfer Learning Genetic Programming

Yilin Liu

Department of Electronic and
Electrical Engineering
Brunel University of London
London, United Kingdom
Yilin.Liu@brunel.ac.uk

Daniil Hulak

Department of Electronic and
Electrical Engineering
Brunel University of London
London, United Kingdom
Daniil.Hulak@brunel.ac.uk

Zhengwen Huang

Department of Electronic and
Electrical Engineering
Brunel University of London
London, United Kingdom
Zhengwen.Huang@brunel.ac.uk

Gareth Taylor

Department of Electronic and
Electrical Engineering
Brunel University of London
London, United Kingdom
Gareth.Taylor@brunel.ac.uk

Abstract—Accurately predicting photovoltaic (PV) power generation is crucial for optimizing energy allocation and integrating solar energy into smart grids. PV generation forecasting faces challenges due to varying forecasting horizons, seasonal changes, and location-specific environmental factors. Transfer learning can improve accuracy and reduce computation by using knowledge from related tasks. Genetic Programming (GP) offers transparent, interpretable symbolic regression models compared to black-box methods. In this paper, a transfer-learning-based GP is applied to the power generation forecasting model of PV installation across different seasons. In the proposed method, mutual information is employed to identify the useful knowledge from constructed models as the source domain, and captured shared generation patterns are then embedded into the initial population of the GP model for the target domain, guiding the search process. The proposed method is evaluated on a case study leveraging the homologous power generation patterns across different seasons for the same PV installation to assist in constructing forecasting models. Experiments on real-world seasonal data show the method outperforms state-of-the-art algorithms, improving both accuracy and model explainability. These results highlight the potential of transfer learning in GP for PV installation generation forecasting, offering both performance improvements and model transparency, which are crucial for real-world deployment and interpretability.

Keywords—Photovoltaic Installation, Transfer Learning, Genetic Programming

I. INTRODUCTION

The Photovoltaic (PV) installations play a vital role in the renewable power systems, especially with the growing emphasis on eco-friendly energy. Accurate forecasting of PV power generation is essential for ensuring the power systems' resilience and reliability of solar energy integration into the power grid. Moreover, precise forecasting contributes significantly to improving operational efficiency and enabling informed decision-making in energy management and distribution. Efficient computational strategies as well as modern technologies are essential to ensure timely and accurate predictions. There is potential to reduce the computational load of building models for similar PV systems by reusing transferable knowledge, while still adapting to local system dynamics.

Transfer learning can address the research gaps mentioned, leveraging the knowledge from previously solved tasks, which are called the source domain, to address emerging cases as the target domain. Prior studies in transfer learning used for PV installations forecasting tasks are mainly categorised as model transfer based on Neural Network architectures like Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) [1], [2] in which part of the networks are learned first in the source domain and frozen, and then de-frozen some of the layers and relearning them in the target domain to bypass some of the re-learning costs. While these methods can reduce computational load and prove the success of application transfer learning in this application domain, they often lack clear interpretability regarding which parts of the model are being transferred. A highly interpretable model offers more transparent and reliable results, enabling professionals to better understand the underlying mechanisms of the target system and conduct further analyses, such as sensitivity evaluation.

Genetic Programming (GP) [3] provides a viable alternative in this context. Known for its ability to model complex systems, GP not only captures intricate relationships but also provides a level of explainability. Transfer learning has been applied to GP to improve the accuracy and has shown its powerful ability in real-world tasks. However, its application in power system forecasting, particularly in the generation forecasting with GP, has not been widely explored.

To address the research gap mentioned above, this paper proposes a novel application of mutual-information-based transfer learning for GP in the short-term forecasting problem. Mutual information serves as a high-level descriptor of dependency, allowing identification of the beneficial parts of models from source domain tasks. In the proposed method, these high-value segments, determined by their mutual information with the target data, are transferred directly into the target domain, forming part of the initial population. This approach not only reduces the need to rediscover relationships again but also maintains a comparable accuracy of the model. Specifically, in the PV generation forecasting task, the segments of the constructed demand model in locations are analysed by mutual information, and the sub-models with high mutual information value to the target dataset are transferred to the demand modelling process of a similar location. By leveraging mutual

information, the transfer process becomes more efficient and targeted, ensuring that relevant and meaningful relationships are incorporated.

The proposed method was evaluated and compared with the state-of-the-art (SOTA) approaches. The results in this work highlight the potential for applying transfer learning GP with mutual information as an index for identifying useful segments. The contributions of the proposed works are as follows: Propose a novel application of mutual-information-based transfer learning GP in PV generation prediction. Analyse the potential of the GP transfer learning approach in the modelling of power systems.

This work integrates the challenges and requirements in power system modelling with advanced transfer learning techniques, offering a promising pathway to more efficient and cost-effective demand forecasting.

II. STATE-OF-THE-ART

A. Machine Learning Used for PV Installation Generation Prediction

To enhance forecasting accuracy, a wide range of machine learning techniques has been explored. Various types of Neural Networks, like LSTM [4] and kernel-based methods such as Gaussian Processes [5], have been applied to capture temporal dependencies and nonlinear patterns in load data. These diverse techniques contribute to improving predictive performance across different forecasting horizons. References [5] and [6] provide even more detailed introductions to machine learning techniques used for PV power forecasting tasks. Discussed models show a great ability for accurate forecasting; however, once changes are required, the models should be fully retrained for most cases.

Unlike black-box models, GP [8] offers a symbolic, optimisation-driven approach for modeling complex relationships and generating interpretable forecasting models. By evolving and recombining compact code segments—called Building Blocks—GP constructs human-readable solutions, often as mathematical expressions. Its gradient-free search allows for global optimization, making GP well-suited for transparent, application-oriented forecasting tasks.

B. Transfer Learning Applied in the Prediction Models of PV Installation

Transfer learning has been explored as a method to leverage knowledge from related source domains to enhance forecasting performance. Transfer learning techniques can be broadly categorised into several types, including instance transfer, feature transfer, model transfer, and relationship transfer. In the application of power systems, particularly in the forecasting of PV installation generation tasks, model-based transfer learning is one of the most popular methods. Ref [1] uses a pretrained CNN-LSTM hybrid network model from the source domain, and then the model is fine-tuned by the target domain. The algorithm is designed to study the relations between the ambient temperature, global irradiance, and PV output power. This framework shows a better result compared with non-transfer learning and the external learning method. Reference [2] also uses a similar network model combined with a detailed analysis

of feature selection used before training. The pretrained model, using the data from a PV generation simulator, is then used in the target domain, containing limited real-world data but with several layers retrained. An encoder-decoder architecture with a dual attention mechanism is proposed in [9] to predict PV installation generation. In their method, the encoder-decoder module with input and temporal attention modules from the constructed model is transferred to the target domain with a different plant site. The adaptation layer and prediction layer after the transferred model are used to align the temporal feature and make the prediction. Although these methods help to reduce computational costs, due to the black-box-like characteristics of Neural Network-based methods, they often lack transparency in identifying which components of the model are being transferred.

C. Applications of GP in Power Systems

GP provides a viable alternative in this context. Acknowledged for its capacity to model complex systems, GP excels at uncovering non-linear relationships and offers interpretable solutions through its symbolic representation. Given these advantages, GP and its variants such as Gene Expression Programming (GEP) [10], Multi-gene Genetic Programming [11], and Geometric Semantic Genetic Programming [12] have been increasingly applied in power systems, particularly in load forecasting. In terms of constructing a prediction model of PV, GP is applied to the forecasting of output from PV by finding the correlation between meteorological parameters and the thermal [13] or electrical outputs [8]. Transfer learning techniques used in GP have already shown their abilities to control computation efficiency in professional domains like arc route problems [14], etc. However, there has been limited research into integrating transfer learning within GP frameworks applied to power systems.

III. METHODOLOGY

A. Mutual-Information-based Transfer Learning for Genetic Programming

Many research works in the GP research domain prove the positive effects of building blocks during evolution. If we can find those building blocks in the early stage, we can basically guide the evolution process to the destination quickly. Transfer learning offers a promising solution for identifying GP in the early stage of evolution by enabling GP to utilise knowledge gained from past experiences to improve future performance. In the context of GP, transfer learning focuses on identifying and reusing key knowledge fragments – functional components or substructures – that have proven effective in source domains. The core idea is that if meaningful fragments from previously solved problems can be recognised and introduced early in the evolutionary process, they will propagate through the population and significantly boost GP performance on new, target problems. Mutual information is a high-level description of the dependency of two variables. High mutual information indicates a strong dependency of two random variables. This relationship indicator may help us identify the key knowledge from the source domain.

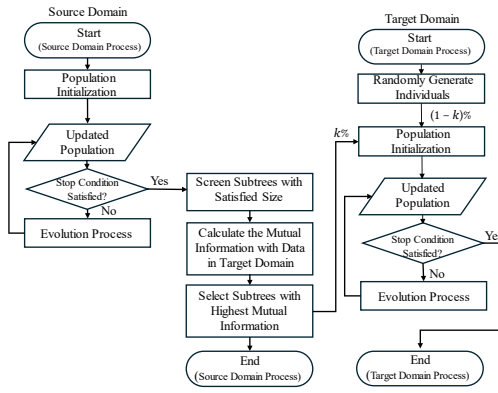


Fig. 1. The proposed transfer learning method in [15], where k is the proportion of biased population in the initial population of the target domain.

Previously, a mutual-information-based transfer learning method was designed to identify and transfer beneficial knowledge fragments in GP from source to target domains [15]. In the proposed method, mutual information between the outputs of subtrees in the source domain and the data in the target domain is calculated to quantify the relevance of each subtree. These subtrees, regarded as knowledge segments, represent potentially transferable structures. Subtrees with higher mutual information scores are considered more relevant to the target task and are selected for transfer. The pipeline of the proposed method is shown in Fig. 1.

In the proposed method, the useful knowledge segments are identified using normalised mutual information:

$$I_N(\hat{Y}; Y) = \frac{I(\hat{Y}; Y)}{H(\hat{Y}; Y)} \quad (1)$$

where $I(\hat{Y}; Y)$ is the mutual information between the predicted data generated by a tree \hat{Y} and target data in the train set Y , $H(\hat{Y}; Y)$ is their joint entropy. The reason to use the normalised mutual information is that by dividing the joint information entropy, both the specificity and redundancy of the predicted model can be emphasised, theoretically improving the performance of the algorithm [16]. A detailed comparison of the performance of using different ways of normalisation methods is introduced in the authors' previous work [15]. The subtrees show high mutual information with the target domain from the population in the last generation in the source domain will be screened out and carried over to a randomly initialised population in the target domain.

1) *Time Complexity*: In terms of the time complexity, in most GP implementations, individuals are evaluated from the lowest subtrees up to the root, enabling memorization and code reuse. The time complexity per generation can be estimated as:

$$O(N \cdot S \cdot M) \quad (2)$$

where N is the population size, S is the average number of subtrees per individual, M is the number of data samples.

In the proposed method, mutual information is calculated only during the last generation of the source domain. The extra cost comes from the binning and sorting of samples. This

additional process has a time complexity of $O(M \log M)$ which only happens once in the last generation of the source domain. Meanwhile, n -top subtrees with the highest mutual information will be screened out, which costs $O(N \cdot S \log n)$ if using Min heapsort. Thus, the additional time complexity for it is:

$$O(N \cdot S \cdot M \log M) + O(N \cdot S \log n) \quad (3)$$

Also, since initial population biasing only affects the initialization phase, it does not increase the time complexity of initialization in the target domain.

2) *Introduced Hyperparameters*: In addition to standard GP hyperparameters, the proposed method introduces three new ones: screened subtree height, number of top-ranked subtrees by mutual information (n), and insertion ration ($k\%$). Their effects are analyzed as follows: For the satisfied size of subtrees, a smaller subtree better aligns with the general definition of Building Blocks in GP and also helps reduce bloat [15]. Therefore, the subtree size should be kept reasonably small. In the initial population of the target domain, there are $k\%N/n$ biased individuals carrying the selected subtree. While too many biased individuals may reduce diversity and limit global exploration, even small fitness improvements from Building Blocks can, according to Schema Theory, spread exponentially through the population. Therefore, both values of $k\%$ and n should be kept small while ensuring the biased individuals have a chance to survive into the next generation. Also, mutual information involves a discretization bin number as a hyperparameter. Since it only affects calculation of mutual information, the method should still reliably capture shared structures with reasonable binning.

B. Problem Formulation

1) *Forecasting Model for PV Installation Power Generation*: The predictive modelling of PV power generation \hat{P}_{PV} can be formulated as a multivariate function $f_{ML}(\cdot)$ that encapsulates the influence of a range of environmental and temporal parameters, including but not limited to solar irradiation and the intensity of ultraviolet radiation. In this research, the variables selected to construct the model are based on [17]. The forecasting model can be expressed as:

$$\hat{P}_{PV} = f_{ML} \left(\begin{array}{c} \text{Month, Day, Time,} \\ \text{Sen_Irr, WS_Solarrad, WS_Solaren,} \\ \text{SAT_glob_hor_irr, SAT_glob_hor_irr_cl} \\ \text{SAT_dif_norm_irr, SAT_dif_hor_irr,} \\ \text{SAT_UVA_irr, SAT_UVB_irr, SAT_UV_irr} \end{array} \right) \quad (4)$$

The description of the variables used in the above forecasting model is shown in Table I. The proposed method will be applied to construct this model.

2) *Transfer Learning Task*: Concerning PV installation power generation, it is observed that while the overall generation profiles of identical PV systems tend to exhibit consistent patterns across different seasons (e.g., summer and winter), the daily power output in each season varies substantially in

temporal distribution. Fig. 2 gives an example of data used in the experiment. These discrepancies are primarily attributed to seasonal fluctuations in environmental factors such as solar irradiation. Therefore, from a theoretical perspective, we aim to identify the shared components of power generation models across different seasons through mutual information analysis. By transferring these common components from already developed models to those corresponding to other seasons where models have not yet been established, we seek to enhance both modelling efficiency and the generalisation ability of short-term PV power forecasting models. In this research, a previously constructed short-term forecasting model for the summer season is employed as a source of transferable knowledge. Through mutual information analysis, we identify and extract knowledge components – manifested as subtrees within the GP model – that demonstrate high relevance to hourly power generation in the winter season. These components are subsequently transferred into the winter forecasting model to enhance its predictive performance and generalisation ability. Thus, the transfer learning task can be represented as:

$$\hat{P}_{PV,winter} = T(K_{MI}(\hat{P}_{PV,summer}, D_{winter}), D_{winter}) \quad (3)$$

where $\hat{P}_{PV,winter}$ and $\hat{P}_{PV,summer}$ are the predictive generation models of PV in winter and summer, respectively, $T(\cdot)$ represents the transfer learning process, $K_{MI}(\cdot)$ denotes the proposed knowledge extraction based on mutual information, and D_{winter} is the winter dataset for the same PV installation.

TABLE I. THE DESCRIPTION OF THE VARIABLES USED.

Annotation	Description	Units
Month, Day, Time	Time variables	-
SEN_irr	Irradiance from PV installation sensor	W/m ²
WS_solarrad	Solar power at the instantaneous moment of the observation	W/m ²
WS_solaren	Total energy from the sun that builds up over an hour	MJ/m ²
SAT_glob_hor_irr	The total solar irradiance incident (direct plus diffuse) on a horizontal plane at the surface of the Earth under all sky conditions	W/m ²
SAT_glob_hor_irr_cl	The total solar irradiance incident (direct plus diffuse) on a horizontal plane at the surface of the Earth under clear sky conditions.	W/m ²
SAT_dif_norm_irr	The direct solar irradiance incident on a horizontal plane normal (perpendicular) to the direction of the sun's position under all sky conditions	W/m ²
SAT_dif_hor_irr	The diffuse (scattered from the original direct path by molecules or particles) solar irradiance incident on a horizontal plane at the surface of the Earth under all sky conditions	W/m ²
SAT_UVA_irr	The ultraviolet A (UVA 315 nm- 400 nm) irradiance under all sky conditions	W/m ²
SAT_UVB_irr	The ultraviolet B (UVB 280 nm- 315 nm) irradiance under all sky conditions	W/m ²
SAT_UV_irr	The ultraviolet radiation exposure index	W/m ²

IV. EXPERIMENT

The proposed method is applied to the PV generation forecasting problem formulated in the previous section. Concretely, the proposed method uses a summer PV generation model to help build the corresponding winter model. By transferring shared information from the same PV installation, it aims to improve prediction accuracy. The method is then compared with SOTA approaches to demonstrate its effectiveness in seasonal PV forecasting.

A. Dataset

The primary generation data used in this study comes from a rooftop PV installation at Brunel University of London (51.5308°N, 0.4740°W) [17]. The system consists of 22 monocrystalline panels with a total nominal capacity of 7.5 kWp, installed on a flat roof covering approximately 300 m². The dataset is supplemented with three sources of weather data: (1) site-specific irradiance measurements from a nearby 3S-IS sensor; (2) ground meteorological data from the Hillingdon Borough weather station via the Visual Crossing platform [18]; (3) hourly satellite-based weather data from NASA's POWER project, accessed using the Data Access Viewer v2.4.14 [19].

The PV summer generation dataset consists of 2,927 data points, covering the periods from June 1st to August 31st, 2023, and from June 1st to June 30th, 2024. The winter dataset contains 2,184 data points, spanning from December 1st, 2023, to February 29th, 2024.

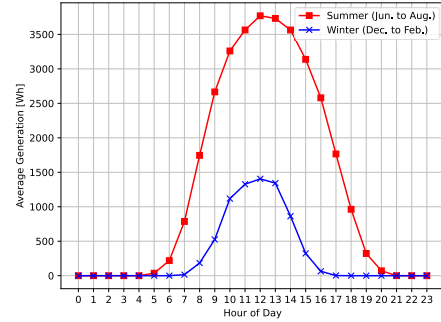


Fig. 2. The hourly average power generation of PV installations in summer (red square) and winter (blue cross) was used in the experiment.

B. Configurations

In the experiment, the configurations for standard GP and the proposed method are listed in Table II. The parameter configurations are based on trials and tests. For these two algorithms, besides all the variables in the dataset, the terminal set consists of ephemeral constants from $[-1,1]$ and π . The division used in the function set is a protected version: if the calculation is invalid, it returns 1. For the proposed transfer learning algorithm, both the source and target domains share the same general configurations. In addition, each run also includes re-executing the source problem and subtree extraction before solving the target. To maintain generalisation and prevent model bloat, only subtrees from the final generation in the source domain, with sizes ranging from 5 to 15, are considered for mutual information analysis with the target domain data. The top 50 subtrees exhibiting the highest mutual information values concerning the target domain are selected. These subtrees are

then used to uniformly generate individuals, which constitute 10% of the initial population in the target domain. It is important to note that mutual information is a metric defined in the discrete domain. In the experiments, this metric is computed by discretising each dataset into 10 equally spaced bins.

For Standard GP and the proposed method, all the experiments are implemented by DEAP [20] 1.4.1 on Python 3.12. If an individual’s fitness or test error compilation fails due to values that exceed Python’s limit during the calculations, the individual is assigned an infinite fitness/test error to indicate the overflow/underflow. In addition to standard GP, the proposed method is compared with several SOTA machine learning algorithms, including Linear Regression, Random Forest, Multi-Layer Perceptron (MLP), AdaBoost, k-nearest Neighbours Regressor (KNN Regressor), and Support Vector Machine Regressor (SVM Regressor). All baseline algorithms are implemented using Scikit-learn [21] version 1.6.1 with default hyperparameters. For the MLP model, the maximum number of iterations is set to 1,000 to ensure convergence. Each algorithm is independently executed 10 times to account for randomness and ensure statistical reliability. To evaluate performance, the Mean Absolute Error (MAE) and the coefficient of determination (R^2) are computed on both the training and test datasets for the results of each algorithm. MAE measures the average errors between predicted and actual values, while R^2 reflects how well the model fits the data [22]. These metrics are then averaged across 10 independent runs to account for variability and provide a more reliable assessment.

V. RESULT ANALYSIS

A. Performance

Following the experimental setup, Table III presents the forecasting performance of winter-season PV generation models. For each evaluation metric, the performance of all algorithms is ranked, with rankings shown as underlined values. Standard GP performs comparably to SOTAs like KNN Regressor and MLP, showing its potential, though it does not achieve the best results on either the training or test set. In contrast, the proposed method, while not having the lowest training error, ranks first on the test set with the lowest MAE and highest R^2 , demonstrating strong generalisation. This confirms the effectiveness of the proposed relationship mining strategy in transferring useful knowledge from the summer model to improve winter forecasting. Among the other models, the SVM Regressor and linear regressor perform noticeably worse, showing the highest MAE and lowest R^2 on both training and test sets. This suggests that linear and kernel-based methods struggle to model the complex and seasonal patterns in PV power generation. The KNN Regressor may be sensitive to the large number of zeros in the dataset caused by the sunlight patterns. These zeros occur regularly due to the daily solar cycle and carry meaningful information, so they cannot be simply treated as noise or omitted. Random Forest, being an ensemble of decision trees focused on local features, achieves the best results on the training set; however, it may be overfit on the test set. Unlike GP, which learns explicit formula structures. Random Forest makes predictions by averaging votes from the “leaf nodes” it has encountered.

In addition, Fig. 3 presents box plots of MAE values across 10 independent runs for both the training and test datasets. The

inset zooms in on the comparison between the standard GP and the proposed method. The proposed method achieves a lower median MAE on the test set, indicating better average predictive performance. However, standard GP shows a narrower spread, suggesting that although its prediction accuracy is not optimal, its performance is slightly more stable across different runs. On the other hand, the proposed method maintains competitive stability while significantly improving prediction accuracy. Taken together, these results suggest that the proposed transfer learning method achieves the best predictive accuracy on unseen data and maintains high robustness and generalisation ability. This supports its suitability for seasonal forecasting tasks where domain shifts exist, but partial structural similarities can be leveraged.

B. Search Space

To evaluate the effectiveness of the proposed transfer learning approach in GP, the search space of the winter PV power prediction task is visualised and analysed. In evolutionary computation, the fitness landscape helps assess problem difficulty—if better fitness often corresponds to smaller individuals, the problem is generally easier to solve [23]. In this analysis, 100,000 individuals are generated using two methods: standard random initialisation and the proposed biasing with transferred subtrees from earlier experiments. The fitness landscape is constructed by recording each individual’s fitness, size, and frequency. This enables a direct comparison of search space characteristics between standard GP and the proposed transfer learning approach. All other settings are consistent with the main experiments to ensure fairness. It can be observed that, compared to randomly initialised populations, initial population biasing, used as the de-abstraction method in the proposed approach, generates individuals with smaller sizes and better fitness. This technique allows the evolutionary process to focus on subspaces with high mutual information, even though they represent only small portions of the search space. According to Schema Theory, individuals with compatible genetic information (i.e., small size and high fitness) can be propagated in subsequent generations. Additionally, the search process in later generations can further adapt based on the knowledge embedded in these individuals, leading to an improved result compared with the standard GP. A theoretical analysis of this technique can be found in the authors’ previous paper [15].

TABLE II. THE EXPERIMENT CONFIGURATIONS FOR THE STANDARD GP AND THE PROPOSED METHOD

Parameters	Configurations
Population size	30,000
Generations	60
Initialization	Half and Half, Depth of tree range = [2,6]
Selection	Tournament, Tournament size = 60
Elitism	On, Hall-of-fame size = 5
Crossover	Standard Crossover, Crossover Rate = 0.9
Mutation	<ul style="list-style-type: none"> • Subtree Mutation, Mutation Rate = 0.08, Depth of mutation tree range = [2,4] • Point Mutation, Mutation Rate = 0.02
Fitness Function	Mean Absolute Error in all fitness cases.
Test Error	Mean Absolute Error in all test cases.
Bloat Control	StaticLimit [3], Max size of tree = 150
Primitive Set	+, −, ×, protective_div, cos, sin, tan, const [−1,1], π
Final Solution	The best individual in the elites after the last generation.

TABLE III. THE PERFORMANCE OF THE PROPOSED METHOD AND ITS COMPARISON WITH SOTAS

Models	Average Performance							
	Train MAE		Test MAE		Train R ²		Test R ²	
	Value	Rank	Value	Rank	Value	Rank	Value	Rank
Linear Regression	34.800	6	73.010	6	0.986	6	-4.838	8
Random Forest	7.195	1	20.800	3	0.999	1	0.989	3
MLP	18.785	4	21.177	4	0.993	3	0.978	5
AdaBoost	132.574	7	136.515	7	0.962	7	0.952	6
KNN	20.974	5	26.974	5	0.989	5	0.983	4
SVM Regressor	221.864	8	234.967	8	0.142	8	0.128	7
Standard GP	18.548	3	19.399	2	0.992	4	0.992	2
Proposed Method	17.912	2	15.618	1	0.994	2	0.994	1

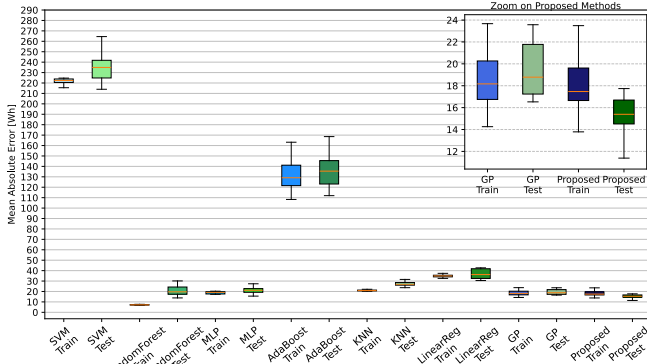


Fig. 3. The box plot with MAE on the training and test sets in 10 runs of the proposed method compared with SOTAs.

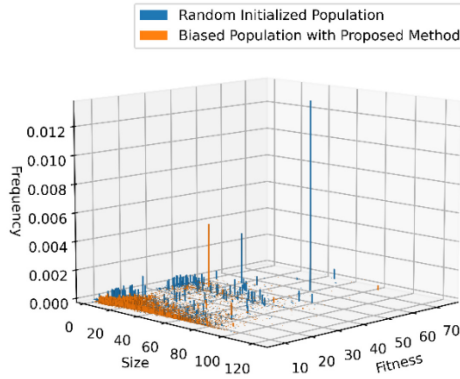


Fig. 4. The initial searching space for the proposed method with recorded extracted subtrees in the previous experiment compared with the randomly initialised population used in standard GP.

C. Sensitivity Analysis

A key feature of GP is its ability to produce human-readable solutions. In the experiment, which involves symbolic regression, each GP individual is a mathematical expression that models the relationship between PV power generation and environmental factors. This inherent interpretability not only allows for accurate predictions but also provides an opportunity for deeper insight into how each input variable contributes to the output. Such a property makes GP especially suitable for further post-hoc analysis, such as sensitivity analysis, which can be used to quantitatively assess the impact of individual environmental variables on the predicted power output. This capability is

valuable in both understanding the model and guiding practical decision-making in PV system management.

In this section, the individual with the best performance on test MAE among 10 runs of the proposed GP-based transfer learning method is picked, which is shown as:

```

multiply(ARG3, cos(add(cos(3.141592653589793), div(ARG11, add(div(subtract(multiply(ARG12,
cos(cos(div(ARG9, ARG8))))), subtract(ARG0, ARG12)), cos(cos(cos(multiply(subtract(multiply(ARG12,
cos(cos(ARG2))), subtract(ARG0, 3.141592653589793))), cos(cos(cos(add(cos(-0.9774192200286607),
div(add(div(subtract(sin(ARG12), ARG9), cos(cos(add(div(ARG9, ARG8), div(ARG11, -
0.9774192200286607))))), div(ARG9, ARG8), ARG4)))))), 3.141592653589793))),
div(cos(add(cos(div(subtract(multiply(cos(ARG2), cos(cos(cos(subtract(multiply(cos(ARG2),
cos(cos(cos(cos(-0.9774192200286607))))), subtract(ARG0, 0.1735669412222145))))), ARG0),
cos(cos(add(-0.9774192200286607, div(add(div(subtract(cos(add(div(ARG9, ARG8), ARG12),
subtract(ARG0, tan(add(3.141592653589793, add(multiply(3.141592653589793, multiply(-
0.9774192200286607, multiply(multiply(3.141592653589793, -0.9774192200286607)), -
0.9774192200286607)), ARG10))))), cos(ARG0)), 3.141592653589793), ARG4))))), multiply(-
0.9774192200286607, multiply(multiply(3.141592653589793, -0.9774192200286607),
0.9774192200286607))), subtract(multiply(0.1735669412222145, ARG9),
div(div(subtract(-0.9774192200286607, ARG4), cos(tan(cos(multiply(multiply(ARG8, ARG12),
cos(cos(3.141592653589793))))), ARG3))))))

```

Fig. 5. The best test MAE individual from 10 runs in the proposed method.

Sobel sensitivity analysis with 1024 samples is applied to the above equation; the result is shown in Table IV. Based on the result, it can be identified that ARG3 and ARG9 are the most influential variables in predicting PV power generation during the winter season, with sensitivity scores of 0.7252 and 0.1877, respectively. This indicates irradiance-based variables play the most important role in the model. In contrast, variables such as *Day* and *WS_solaren* showed zero sensitivity and were excluded from the final model, indicating minimal impact on prediction. This likely results from the dominance of *SEN_irr*, which, being installed directly on the PV system, provides more accurate irradiance data. Its proximity gives it a competitive contribution, providing useful information, making other irradiance-related variables redundant. Since the other radiance variables capture temporal patterns, pure time variables like *Day* provide limited additional information. Findings suggest that prioritising features with high impact can enhance model accuracy, while low-impact variables may be excluded to reduce complexity and overfitting. This highlights GP's inherent capability to automatically perform feature selection by evolving models that emphasise only the most relevant inputs. The sensitivity results highlight the advantage of GP's transparent, mathematical expressions. Unlike black-box models, GP solutions are easier for humans to interpret, allowing deeper insight into the underlying physical system. This transparency enhances model trust, supports validation, and aids practical decisions in PV system design and management.

TABLE IV. SENSITIVITY ANALYSIS ON THE BEST INDIVIDUAL OF THE PROPOSED METHOD

Annotation	Variable	Sensitivity
ARG0	Month	-0.0048
ARG1	Day	0.0000
ARG2	Time	0.0026
ARG3	SEN_irr	0.7252
ARG4	WS_solarrad	-0.0027
ARG5	WS_solaren	0.0000
ARG6	SAT_glob_hor_irr	0.0000
ARG7	SAT_glob_hor_irr_cl	0.0000
ARG8	SAT_dif_norm_irr	-0.0020
ARG9	SAT_dif_hor_irr	0.1877
ARG10	SAT_UVA_irr	0.0022
ARG11	SAT_UVB_irr	-0.0001
ARG12	SAT_UV_irr	-0.0006

VI. CONCLUSION

In conclusion, this research proposed a method of short-term prediction of electrical power generation of PV using mutual-information-based transfer learning GP. The proposed method leverages the similarity in models between different seasons, extracting useful information from the constructed seasonal model to target the unconstructed seasonal prediction model. This research highlights the potential of the application of GP and mutual-information-based transfer learning in identifying the key relationships between parameters and constructing a powerful prediction model of PV. The experiments on the real-world PV power generation dataset show the outstanding performance of the proposed method compared to standard GP and other SOTAs like Random Forest, KNN regressor, and MLP. In the construction of the winter prediction model, the proposed method shows the lowest MAE and highest R^2 , indicating its distinctive accuracy and generalisability.

Furthermore, performance consistency across repeated trials and favourable search space characteristics illustrated the robustness and efficiency of the proposed approach. In addition, the sensitivity analysis of the best individual generated by the proposed method reveals the most influential factors in PV power generation during the winter season. This analysis highlights the advantage of GP's symbolic nature, which enables human users to gain deeper insights into the constructed model. The ability to trace and interpret model behaviour not only enhances trust in the model but also supports informed decision-making in real-world PV system planning and management.

ACKNOWLEDGMENT

The weather data used was obtained from the NASA Langley Research Center (LaRC) POWER Project funded through the NASA Earth Science/Applied Science Program. The authors also thank the university for providing the data and for its support throughout the writing of this paper.

REFERENCES

- [1] G. Almonacid-Olleros, G. Almonacid, D. Gil, and J. Medina-Quero, "Evaluation of Transfer Learning and Fine-Tuning to Nowcast Energy Generation of Photovoltaic Systems in Different Climates," *Sustainability*, vol. 14, no. 5, 2022.
- [2] A. Bellagarda, D. Grassi, A. Aliberti, L. Bottaccioli, A. Macii, and E. Patti, "Effectiveness of neural networks and transfer learning to forecast photovoltaic power production," *Appl. Soft Comput.*, vol. 149, p. 110988, Dec. 2023.
- [3] John R. Koza, *Genetic programming: on the programming of computers utilizing natural selection*. MIT Press, 1992.
- [4] K. Wang, X. Qi, and H. Liu, "Photovoltaic power forecasting based LSTM-Convolutional Network," *Energy*, vol. 189, p. 116225, Dec. 2019.
- [5] F. Najibi, D. Apostolopoulou, and E. Alonso, "Enhanced performance Gaussian process regression for probabilistic short-term solar output forecast," *Int. J. Electr. Power Energy Syst.*, vol. 130, p. 106916, Sep. 2021.
- [6] K. J. Iheanetu, "Solar Photovoltaic Power Forecasting: A Review," *Sustainability*, vol. 14, no. 24, 2022.
- [7] A. Mellit, A. Massi Pavan, E. Ogliaari, S. Leva, and V. Lughi, "Advanced Methods for Photovoltaic Output Power Forecasting: A Review," *Appl. Sci.*, vol. 10, no. 2, 2020.
- [8] M. Russo, G. Leotta, P. M. Pugliatti, and G. Gigliucci, "Genetic programming for photovoltaic plant output forecasting," *Sol. Energy*, vol. 105, pp. 264–273, Jul. 2014.
- [9] Y. Tang, K. Yang, S. Zhang, and Z. Zhang, "Photovoltaic power forecasting: A dual-attention gated recurrent unit framework incorporating weather clustering and transfer learning strategy," *Eng. Appl. Artif. Intell.*, vol. 130, p. 107691, Apr. 2024.
- [10] S. S. Sadat Hosseini and A. H. Gandomi, "Short-term load forecasting of power systems by gene expression programming," *Neural Comput. Appl.*, vol. 21, no. 2, pp. 377–389, Mar. 2012.
- [11] C. Emeksiz, "Multi-genetic programming based improved innovative model for extrapolation of wind data at high altitudes, case study: Turkey," *Comput. Electr. Eng.*, vol. 100, p. 107966, May 2022.
- [12] M. Castelli, L. Vanneschi, and M. De Felice, "Forecasting short-term electricity consumption using a semantics-based genetic programming framework: The South Italy case," *Energy Econ.*, vol. 47, pp. 37–41, Jan. 2015.
- [13] A. Sohani and H. Sayyaadi, "Employing genetic programming to find the best correlation to predict temperature of solar photovoltaic panels," *Energy Convers. Manag.*, vol. 224, p. 113291, Nov. 2020.
- [14] M. A. Ardeh, Y. Mei, M. Zhang, and X. Yao, "Knowledge Transfer Genetic Programming With Auxiliary Population for Solving Uncertain Capacitated Arc Routing Problem," *IEEE Trans. Evol. Comput.*, vol. 27, no. 2, pp. 311–325, 2023.
- [15] Yilin Liu, Gareth Taylor, and Zhengwen Huang, "Novel Application of Mutual Information in Transfer Learning for Genetic Programming," in *Proceedings of Genetic and Evolutionary Computation Conference (GECCO) Companion*, ACM, Jul. 2025, p. 4.
- [16] S. W. Card and C. K. Mohan, "Information theoretic indicators of fitness, relevant diversity & pairing potential in genetic programming," in *2005 IEEE Congress on Evolutionary Computation*, Sep. 2005, pp. 2545–2552 Vol. 3.
- [17] D. Hulak, Y. Xie, and G. Taylor, "Performance Analysis of Photovoltaic Installations Based on Machine Learning Techniques," in *Proceedings of 2024 59th International Universities Power Engineering Conference (UPEC)*, Sep. 2024, pp. 1–6.
- [18] Visual Crossing Corporation, "Visual Crossing Weather (2023-2024)." [Online]. Available: www.visualcrossing.com
- [19] National Aeronautics and Space Administration (NASA) Langley Research Center (LaRC), "Prediction Of Worldwide Energy Resources (POWER) Project."
- [20] Félix-Antoine Fortin, François-Michel De Rainville, Marc-André Gardner Gardner, Marc Parizeau, and Christian Gagné, "DEAP: evolutionary algorithms made easy," *J Mach Learn Res*, vol. 13, no. 1, pp. 2171–2175, 2012.
- [21] Fabian Pedregosa *et al.*, "Scikit-learn: Machine Learning in Python," *J Mach Learn Res*, vol. 12, pp. 2825–2830, 2011.
- [22] D. Hulak and G. Taylor, "Investigating an Ensemble of ARIMA Models for Accurate Short-Term Electricity Demand Forecasting," in *2023 58th International Universities Power Engineering Conference (UPEC)*, Sep. 2023, pp. 1–6.
- [23] W. B. Langdon and R. Poli, "The Genetic Programming Search Space," in *Foundations of Genetic Programming*, Berlin, Heidelberg: Springer Berlin Heidelberg, 2002, pp. 113–132.