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Effective Input Dataset Identification Methodology for Accurate Prediction of Local PV Power Production

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Abstract—Local photovoltaic (PV) systems are playing a considerable role globally as a power resource and constituent element of the smart grid. Nevertheless, PVs may cause significant problems to the electric grid. This is due to the high variability of the PV power that is instigated by intermittent environmental conditions. Accurate prediction of PV power is very important to operate power grids containing high penetration of PVs. Most prior approaches have focused on forecasting the collective quantity of solar power generation at national or regional scale and disregarded the local PVs that are installed mainly for local electric supply. This paper devises an effective input dataset identification methodology (IDIM) to find the most significant and non-repetitive input variables for accurate prediction of the power production of local PVs. In the devised methodology, the Binary Genetic Algorithm (BGA) is used for the input variable identification and Support Vector Regression (SVR) is employed for evaluating the fitness of the input datasets. The devised methodology is implemented and validated based on actual local PVs (building rooftop PVs) located in the Otaniemi area of Espoo, Finland. The results are compared with those obtained by conventional counterparts and manifest outperformed performances.

Keywords—BGA, fitness evaluation measure, input dataset identification, local PV, prediction, renewable energy, smart grid, SVR.

I. INTRODUCTION

Deployment of renewable energy resources, predominantly solar energy, has received much attention globally. This is because electricity generation from solar energy is clean, accessible everywhere, has a simple structure and does not require a prime-move. Although PV power has significant environmental benefits and is a likely source of energy for the future, its uncertainty due to intermittency of weather variables makes it more challenging to implement, as the uncertainty of the generation causes big challenges for grid stability and control. This problem can be addressed through the development and integration of accurate PV power prediction tools.

The choose of appropriate input predictor subset is currently a very relevant research and development (R&D) issue in the area of PV power prediction. Finding the best predictor dataset from a big size of predictor space enhances forecasting accuracy. This initiates R&D in effective and appropriate input dataset identification (IDI) methods for improving the accuracy of PV power prediction. Input dataset identification is a process of picking a subset of the most significant variables for a prediction or classification task. IDIMs are important for prediction models mainly to lower computing time and storage memory size, increase generalization and interpretability, simply complexity, and reduce overfitting.

The central logic when developing an IDIM is that the initial dataset contains some features that are either repetitive or unimportant and can thus be removed without causing significant

destruction of information. A number of researches have shown that repetitive and unimportant variables decrease the performance and generalization competence of forecast systems. That is why, recently, IDIM researches are becoming quite prominent.

The methods for accurate prediction of the power output of local PVs have a big influence on improving the commercial advantages and quality of PV-integrated energy systems. Nevertheless, IDIMs and PV power prediction tools have not yet deeply investigated and the findings so far in the area are not satisfactory. Most previous studies on PV power prediction employed a fixed and subjective set of predictors. They did not use IDIMs to select the forecasting system input features, which would have a substantial enhancement on prediction performance.

The focus of this study is to devise and develop an IDIM for accurate short-term prediction of power production of local PVs in general and building rooftop PVs in particular.

Prediction accuracy is the central goal of almost all prediction researches. As thoroughly shown in [1] and [2], the accuracy of forecasting approaches relies on the feature scope that is formed via the initial feature sets and IDIMs. IDI is typically used in ML applications as one of the preprocessing tasks, where a feature subset is established by eradicating variables with inferior or insignificant value and highly repetitive [3]. Nevertheless, only quite few prediction approaches have performed IDI ahead of fitting PV power forecasting models.

Various metaheuristic optimization techniques have been employed as search methods for IDI. For example, Particle Swarm Optimization (PSO) [4], Ant Colony Optimization (ACO) [5] and Genetic Algorithm (GA) [6]. GA has been widely used due to its higher suitability and effective searching capability. It belongs to the class of the artificial intelligent (AI) searching algorithms and has been successfully applied for solving numerous optimization problems [7].

This study proposes a hybrid ML-based IDIM using the combination of Binary Genetic Algorithm (BGA) and Support Vector Regression (SVR) for accurate short-term prediction of the power output of local PVs. BGA is a type of GA that functions by first encoding the feature space (candidate solutions) in binary bitstrings. This makes the BGA even more suitable for IDI tasks than the traditional GA. In the proposed hybrid BGA-SVR-based IDIM, the BGA is used to select the most significant and non-repetitive variables, while the SVR is employed to measure the fitness of the variables for the BGA execution.

The paper examines and suggests the significance of an effective IDIM and enabling techniques for accurate PV power prediction, devises and implements effective and efficient IDIM for PV power prediction, and boosts prediction accuracy via the use of IDIM ahead of learning PV power prediction models.

The remaining parts of the paper are outlined below. Section II presents the relevant prior works on IDIM. Section III provides the data and states the IDI problem. Sections IV and V describe the working principle and mathematical modeling the BGA and SVR, respectively. Section VI discusses the devised BGA-SVR-based IDIM. The results and discussions are provided in Section VII. The paper is concluded in Section VIII.

II. LITERATURE

IDIMs can be categorized as filter, wrapper and embedded methods [1]. Filter methods do not rely on any forecast model and they order variables based on statistical behavior. They use a correlation value to grade a predictor subset. The Filter IDIM comprises correlation-based [8], mutual information-based [9], and principal component analysis-based methods [10]. Wrapper methods assess variable subsets depending on their value to a particular predictor or classifier. They assume the IDI as a searching problem that handles numerous combinations of variables, measured, and compared with other combinations. Compared to the filter methods, wrapper methods show better performances because several predictor subsets are measured by the forecast model at every step [11]. Embedded techniques combine the variable selection task into the forecast model learning task. For example, the regularization technique [1] is one type of an embedded IDIM.

Table I provides the recent IDIMs for prediction problems.

TABLE I. SUMMARY OF IDIMs

Application	Type of IDIM	References
Power systems	Filter	[8], [12], [13]
	Wrapper	[14], [15]
Energy systems	Filter	[16] [17]
	Wrapper	[18] [19]

Among the wrapper IDIMs given in Table I, the GA-based IDIMs show best performances in eradicating replicated variables. Reference [17] proposed importance based IDIM for PV power prediction employing a random forest algorithm. Reference [19] proposed a combination of GA and Gaussian Process Regression (GPR) for IDIM in PV power prediction. It used the GPR as a fitting model to formulate the GA fitness function. Reference [20] proposed the hybridization of GA and ACO for IDIM in electricity demand forecasting. Reference [21] proposed the combination of GA and SVR for IDI to forecast hotel-room booking. Reference [22] applied a GA-based IDIM to forecast the demand of Chinese retail industries. Reference [23] devised an improved GA for IDI in the demand forecasting in the health sector.

In the IDI process, the variables are sorted and chosen based on their evaluated values of the fitness function. The subset of variables that gives the best value of the fitness function is selected. This paper employs the residual (error) of the SVR model as the fitness function of the BGA.

The literature review in this paper shows that the traditional GA with the standard framework is employed for IDI by most researches [15]. The traditional GA functions with the real-valued variables to reduce the fitness function. This decreases the efficiency of the IDI and causes computation burden. This problem is addressed in this paper by substituting the traditional GA by the BGA and combining it with the effective fitness evaluation measure (SVR residual).

III. INPUT DATASET IDENTIFICATION PROBLEM

The candidate variables of the original feature space for this IDI work includes seasonal and weather variables. The variables f_i , $i = 1, 2, \dots, 20$, in Table II represent the candidate variables.

Hence, the feature space is a matrix of order $m \times n$, where $m = 192$ is the number of observations, which is eight-day (two days from each season) hourly sample of the features and $n = 20$ is the number of candidate features.

TABLE II. PREDICTOR PACE OF THE IDI PROBLEM

Input Predictor Index	Predictor (f_i)	Unit/Scale	Data Category
1	Hour of the day	1-24	Seasonality/calendar
2	Month of the year	1-12	
3	Season of the year	1-4	
4	Air temperature	°C	Weather
5	Dew point	°C	
6	Humidity	%	
7	Precipitation	mm/h	
8	Snow depth	cm	
9	Air pressure	hPa	
10	Horizontal visibility	m	
11	Wind direction	deg	
12	Wind speed	m/s	
13	Gust speed	m/s	
14	Cloud cover	0-8	
15	Diffuse solar radiation	Watt/m ²	
16	Direct solar radiation	Watt/m ²	
17	Global solar radiation	Watt/m ²	
18	Long wave solar radiation	Watt/m ²	
19	UV radiation index	≥ 0	
20	Sunshine duration	s	

In this paper, the optimization problem formulated in (1) is solved in order to find the most significant and non-repetitive prediction input dataset from the set of the candidate variables (original dataset) given in Table II.

Input Dataset (Predictor) Identification Problem:

Given that:

$$f_r \in \mathbb{Z}^+, 1 \leq f_r \leq 20, \text{ and } \beta \in \mathbb{R}^+ \ni 0 \leq \beta \leq 100 \quad (1)$$

where, f_r is the number of features in the reduced dataset and β is the forecasting error (in %). Find a prediction input dataset of f_i from Table II such that the objectives β and f_r are minimized.

IV. BINARY GENETIC ALGORITHM (BGA)

GA is a population-based metaheuristic optimization technique that was motivated by the Charles Darwin theory of human evolution and genetics theory [24]. The GA operates on the chromosomes (candidate solutions) to create a new population (offsprings) through its three genetic operators - selection, crossover and mutation. The fitness of the chromosomes is evaluated using a fitness function. The fitness function gives numerical values that is used for ranking the chromosomes. BGA is a type of GA that operates by first encoding the chromosomes as bitstrings to minimize or maximize the objective function. It is more efficient and stable than the standard real-valued GA. It also reduces computation burden and time. The flowchart of the BGA is shown in Figure 1.

Figure 1. Flowchart of BGA for IDI

V. SUPPORT VECTOR REGRESSION (SVR)

SVR is a non-parametric technique that fundamentally depends on kernel functions. Vapnik *et al.* [25] created the essentials of SVRs in 1995. SVRs are getting substantial credit currently due to many evident features and favorable performances. SVR has been effectively applied to perform predictions, classifications and clustering tasks. The SVR model is based on the structural-risk-minimization (SRM) theory that has been demonstrated to be superior to the standard empirical-risk-minimization (ERM) theory employed by ANNs [26].

The SVR basic operational principle is mapping datasets to higher dimension representative hyperplanes using nonlinear mappings or approximations. Linear-regressions in the upper-dimension hyperplanes are related to non-linear regressions in the lower-dimension plane as expressed underneath [27].

$$y(x) = w \cdot \Phi(x) + b; \Phi: R^n \rightarrow R^N \quad (2)$$

where, $y \in R^N$ is a training target; $x \in R^n$ is a training input (predictor); b is a bias parameter; $w \in R^N$ is weight/coefficient parameter; $\Phi(x)$ is a non-linear mapping-function; and $\Phi: R^n \rightarrow R^N$ is a non-linear mapping.

A particular SVR known as linear-epsilon-insensitive SVR (ϵ -SVR) is employed in this paper due to its scarceness representation capacity. The ϵ -SVR objective function is described based on the ϵ -insensitive loss-function. The SVR model parameters, w and b , can be obtained optimally by solving the constrained fitness function formulated below.

$$\begin{aligned} \min \quad & \left\{ \frac{1}{2} w^T w + \gamma \sum_{i=1}^N (\xi_i + \xi_i^*) \right\} \\ \text{subject to: } & y_i - w \cdot \Phi(x_i) - b \leq \varepsilon + \xi_i \\ & w \cdot \Phi(x_i) + b - y_i \leq \varepsilon + \xi_i^* \\ & \xi_i, \xi_i^* \geq 0 \end{aligned} \quad (3)$$

where, ξ_i and ξ_i^* are auxiliary parameters; γ is a normalization parameter; N is the dataset length; and ε is a loss parameter.

The optimization problem given by (3) is a quadratic programming type, and is solved by solving its equivalent dual-problem formulated beneath.

$$\begin{aligned} \min \quad & \left\{ \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N (\alpha_i - \alpha_i^*) \cdot \Phi(x_i, x_j) \cdot (\alpha_j - \alpha_j^*) - \right. \\ & \left. \sum_{i=1}^N (\alpha_i + \alpha_i^*) \cdot \varepsilon + \sum_{i=1}^N (\alpha_i - \alpha_i^*) \cdot y_i \right\} \\ \text{subject to: } & \sum_{i=1}^N (\alpha_i - \alpha_i^*) = 0; \alpha_i, \alpha_i^* \geq 0 \end{aligned} \quad (4)$$

Solving for the positive Lagrange-multipliers $(\alpha_i - \alpha_i^*)$, the final expression of the SVR output y is given by:

$$\hat{y}(x) = \sum_{i=1}^N (\alpha_i - \alpha_i^*) \cdot K(x, x_i) + b \quad (5)$$

where, $K(x_i, x_j) = \Phi(x_i) \cdot \Phi(x_j)$ is called the SVR kernel. The RBF kernel is employed in this paper and it is defined as follows:

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{\sigma^2}\right) \quad (6)$$

Here, σ is a Gauss parameter (width of RBF kernel) and defines the impact area of the support vectors in the training domain.

The SVR parameters are obtained by solving the optimization problem described in (3).

VI. PROPOSED IDIM

As abovementioned, the proposed IDIM for PV power prediction is based on the combination of the BGA and SVR (BGA-SVR-based

IDIM). Figure 2 shows the flowchart for the detail operating mechanism of the proposed BGA-SVR-based IDIM.

Figure 2. Flowchart of BGA-SVR-based IDIM

There are five crucial sub-tasks in the BGA: chromosome encoding, fitness evaluation, selection technique, genetic operators, and termination condition. An initial population is created and evaluated employing the fitness function. A gene value of '1' designates the particular variable pointed by the position of the '1' is selected for the fitness assessment. While a value of '0' indicates the specific variable is not selected.

The chromosomes are tested based on their fitness values. The top n fittest offsprings (Elitism of size n) are selected to continue with the following generation. The remaining offsprings in the population genetically move via the crossover and mutation operators to generate crossover and mutation offsprings, respectively. The selection, crossover and mutation offsprings are then form the new population (generation) [24], [28] – [29].

In this paper, the fitness of the chromosomes is evaluated using the SVR model. The BGA fitness function is formulated by the mean squared error (MSE) of the SVR model predictive residuals. That is, the MSE of the actual target and the SVR model output is calculated for every variable subset given in Table II. The fitness function is expressed as follows:

$$fit = \frac{1}{n} \sum_{i=1}^n (T_i - y_i)^2 \quad (7)$$

where, T is a vector of target values (PV power) and n is the number of samples.

The goal of the BGA is to minimize the fitness function (7) by selecting a feature subset with the best fitness (lowest MSE) over iterations.

The BGA parameters employed in this paper are given in Table III.

TABLE III. BGA PARAMETERS

Parameter	Value
Population size	20
Genomelength	20
Population type	Bitstring
Fitness function	SVR model residual or error
Number of generations	100
Stall Generation Limit	50
Selection mechanism	Tournament selection
Tournament size	2
Mutation function	Uniform mutation
Mutation rate	0.1
Crossover function	arithmetic crossover (logical XOR)
Crossover fraction	0.8
Elite count	2

The BGA stops when it reaches at a desired optimal point. The optimal point associates with the desired input dataset in question. Following the BGA convergence, the chromosome that achieved the best fitness value is selected and decoded to obtain the desired input dataset (predictor subset) as illustrated in Figure 3.

Figure 3. Final predictor subset decoding

VII. EXPERIMENTAL RESULTS AND VALIDATION

In this study, the hybrid BGA-SVR-based IDIM is developed and validated based on a local PV system installed on a building rooftop located in the Otaniemi area of Espoo, Finland. The PV system has a peak production capacity of 4.3kW.

The empirical results achieved by the proposed IDIM are presented in Table IV.

TABLE IV. IDI RESULTS

Selected Predictor Dataset	Best Fitness ($\times 10^{-3}$)	Without IDIM ($\times 10^{-3}$)
$\{f_1, f_2, f_3, f_4, f_8, f_{14}, f_{17}, f_{20}\}$	2.7	7.6

As shown in Table IV, the number of predictors chosen by the proposed IDIM is considerably lower than the size of the predictor space. This can be due to the availability of irrelevant and redundant information by most of the variables in the original predictor space. The BGA-SVR finally selects the predictor subset which contains the most significant and non-repetitive variables. A predictor input dataset consisting of predictors 1, 2, 3, 4, 8, 14, 17, and 20, which designate the hour of the day, month of the year, season of the year, ambient air temperature, snow depth, cloud cover, global solar radiation, and sunshine duration, respectively, is selected by the devised BGA-SVR-based IDIM. This selected predictor input dataset can therefore establish the input dataset for accurate PV power prediction.

The enhancement in fitness value (MSE) using the BGA-SVR IDIM algorithm selected predictor subset to fit the PV power

production by the SVR model is 64.5% over the initial predictor dataset (without IDIM).

To validate the BGA-SVR IDI work in this paper, the input predictor dataset obtained by the proposed BGA-SVR IDIM are compared with datasets obtained using other two conventional IDIMs, namely: Correlation-based input dataset identification methodology (C IDIM) and Neighborhood Component Analysis Regression-based input dataset identification methodology (NCA IDIM).

The Correlation-based IDIM first calculates the Pearson and Spearman correlations of each predictor with the target, and it then takes the maximum of the two correlation coefficients. A predictor with correlation value greater than a given threshold can be selected as an important predictor and involved in the final predictor subset. A threshold correlation value of 0.20 is used to choose the relevant predictors in this paper. According to the correlation-based method, predictors 4, 5, 6, 8, 15, 16, 17, 18, 19, and 20 are selected to constitute the input variables for the PV power prediction.

The NCA IDIM is based on the neighborhood component analysis (NCA) regression model fitted over the predictor subsets versus target dataset. The NCA IDIM obtains the predictor weights using a diagonal adaptation of the NCA regression model. The model realizes IDI by regularizing the predictor weights. The predictor weight specifies the strength of the relationship of the predictor with the target. Predictors whose weight value is not designated by zero are selected by this technique. Hence, according to the NCA regression model based IDIM, predictors 12, 17 and 19 are chosen.

Table V provides the performance comparison of the IDI results by the devised technique and the other two methods.

TABLE V. COMPARISON OF IDI RESULTS

Selected Predictor Subset			Best Fitness ($\times 10^{-3}$)		
BGA-SVR IDIM	C IDIM	NCA IDIM	BGA-SVR IDIM	C IDIM	NCA IDIM
$\{f_1, f_2, f_3, f_4, f_8, f_{14}, f_{17}, f_{20}\}$	$\{f_4, f_5, f_6, f_8, f_{15}, f_{16}, f_{17}, f_{18}, f_{19}, f_{20}\}$	$\{f_{12}, f_{17}, f_{19}\}$	2.7	3.8	5.5

As shown in Table V, the devised BGA-SVR-based IDIM achieved the predictor dataset with the best fitness value (lowest MSE). Hence, the predictor dataset selected by the proposed IDIM contains more significant and nonredundant variables than the other methods. That means, a PV power prediction model whose input dataset contains the predictor input dataset obtained by the devised BGA-SVR IDIM can achieve the most accurate forecasting.

VIII. CONCLUSION

This paper devised and implemented a BGA-SVR based input predictor dataset identification methodology for accurate short-term PV power prediction. The methodology includes the use of an SVR fitness function to choose a combination of predictor datasets from a given original predictor dataset. The devised BGA-SVR-based methodology has given an input dataset that resulted in a better fitness (lower MSE value) than the original predictor dataset. It is inferred that a PV power prediction model whose input dataset comprises the predictor inputs found by the proposed BGA-SVR-based input dataset identification methodology can achieve accurate prediction results. For comparison and validation purposes, the input dataset selected by two other methods were investigated. The BGA-SVR selected inputs outperformed the other inputs with respect to the MSE fitness function formulated using the SVR model.

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