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Availability predictions of solar power plants using multiple regression and neural networks: an analytical study

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Abstract

This analysis aims to develop an efficient mathematical model for prediction of the system availability of a solar photovoltaic power plant under the concept of redundancy and exponentially distributed random variables. For this objective, a stochastic model of the photovoltaic power plant is created with the help of the Markov birth-death technique. It is assumed that all the repairs are perfect and random variables statistically independent. The predictive techniques, namely regression analysis and artificial neural networks are used to predict the availability of the PV power plant in different experimental setups with the help of SPSS software. The impact of failure and repair rates on the availability of the PV power plant investigated. Experimental data used to calculate the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) of both predictive techniques. It is identified that the MAE and RMSE of the regression model are less in comparison to the ANN model. So, the regression model outperforms ANN in the performance prediction of PV power plants. The outcomes of this study may help design PV solar plants and plan maintenance strategies for solar PV power plants.

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Keywords: Solar PV power plant, Artificial neural networks, Regression model, Markovian approach

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1. Introduction

Due to its abundance, sustainability, and low environmental impact, solar energy is an important source of energy generation among renewable energy sources. It reduces dependency on fossil fuels, decreases greenhouse gas emissions, and lessens climate change by providing a clean, inexhaustible source of power. Solar energy has a significant growth on a global scale, with installed capacity surpassing 1,200 GW by 2023, because of an 80% decrease in costs over the past ten years. It contributes about 4-5% of the world's electricity. Its adoption is highest in China, the U.S., and India. Due to reduced prices and better financial conditions, markets in Africa, Southeast Asia, and Latin America are also increasing very fast. Solar energy is projected to overtake all the other sources of electricity and become the biggest electricity source by 2050. Solar photovoltaics (PV) is a versatile technology known for its increasing global demand for sustainable and renewable energy sources. It is also known for its modularity which allows large-scale manufacturing plants to benefit from economies of medium and small-scale development. PV technology is used in many different applications because of its adaptability, ranging from large utility-scale power generation connections to tiny residential rooftop systems. The core of solar PV technology is the photovoltaic effect. In this effect, photovoltaic cells or solar cells are used to convert light energy into electrical energy. Semicon-

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ductor materials like silicon are used to make these solar cells. When semiconductor material is struck by the photons of sunlight, its electrons gain energy from these photos. This energy transfer excites the electrons, causing them to move and create an electric current. The electric current produced by solar panels can be used instantly or stored in batteries for later use. Due to the involvement of numerous components, it becomes difficult to manage a photovoltaic (PV) power plant. Therefore, it becomes important to ensure their high reliability. Several researchers tried to enhance the availability and reliability of solar power plants through the development of various mathematical models under various sets of assumptions.

The development of technology made computational work simple, and industries are now using advanced analysis techniques like machine learning (ML), deep learning, and soft computing techniques to predict the performance of systems and design new intelligent systems. Reliability and availability are still core measures to evaluate the performance of these intelligent systems. Rajpal *et al*. [1] focused on measures like reliability, availability, and maintainability to model a complex and repairable system using an artificial neural network. Adenso-Diaz *et al*. [2] evaluated the impact of supply network characteristics on reliability. According to findings node criticality, network density, and complexity significantly reduce reliability. These findings guide the design of more reliable supply networks. Bose *et al*. [3] used Weibull distribution to examine the reliability and availability of components in a railway diesel locomotive engine for reliability analysis. Nimon *et al*. [4] found alternative indices to multiple linear regression for referring to multicollinearity issues. Fink *et al*. [5] predicted component reliability and degradation by using multilayer feedforward neural networks with multi-valued neurons (MLMVN). MLMVN uses other machine learning methods in prediction accuracy and stability. Kaushik and Banka [6] introduced the approximated artificial neural network (AANN) algorithm for reliability improvement and cost minimization in complex network designs. Ma *et al*. [7] used quantile regression to analyze the effect of primary factors on the distribution of travel times. The results show that quartile regression gives more detailed insights than linear regression. For the testing of the system reliability assessment, Solanki *et al*. [8] used the principal component regression method to optimize the regression model. Bermejo *et al*. [9] focused on the use of artificial neural network (ANN) models for energy and reliability prediction. Wen *et al*. [10] enhanced an optimized neural network (NN) approach for the reliability evaluation of natural corroding gas pipelines. The optimized NN model provides accurate predictions of pipeline reliability over time, by refining training sample sequences and initial parameters. Goyal *et al*. [11] focused on the performance analysis of the physical processing unit within a sewage treatment plant using RAMD methodology. Sayed *et al*. [12] created a stochastic model and used RAM analysis of grid-connected solar PV systems. Also studied is the increasing importance of enhancing the reliability and availability of the system. Jordan *et al*. [13] highlighted the significance of monitoring, maintenance, and installation quality in confirming the optimal performance of PV systems. This study found that 80-90% of PV systems surpass expected production levels, with residential systems having low failure rates compared to commercial systems. Inverters were identified as the most common component to fail, with failure rates between 4%-6%. Kumar *et al*. [14] aimed to enhance the efficiency of soft water treatment and supply plants, by analyzing reliability, availability, and maintainability. Maihulla *et al*. [15] used RAMD to analyze the criticality of sub-assemblies in grid-connected PV systems. The subsystem inverter is found to be the most critical component in PV systems.

Soft computing techniques have been perused by Kumar *et al*. [16] to obtain the reliability of software. An artificial neural network is used to assess predictive power. To determine the most accurate software reliability model, many matrices were studied like MMRE, SD, RSD, and PRED. Cevasco *et al*. [17] identified the critical components of wind turbines through the reliability, availability, and maintainability investigation. Findings indicate the negative effect of offshore environmental conditions on the reliability of turbines. Maihulla *et al*. [18] applied the RAMD approach to improve efficiency and predict the reliability of grid-connected solar PV systems using the Markovian technique. Diamond *et al*. [19] estimated and reviewed the reliability of wind energy generation systems (WEGS) by proposing varying loads on the units. Power generation indices were developed to evaluate and measure the performance of the model, and a stochastic model was used to modulate the WEGS. Sonawane *et al*. [20] used Fault Tree Analysis (FTA) and Fussel-Vesely (F-V) to find out the critical issues like solder bond failure, broken cells, and structural issues of solar photovoltaic systems. Abdulla *et al*. [21] highlighted the need for integrated maintenance approaches, reliability assessments, and predictive maintenance to enhance system efficiency. Petronnijevic *et al*. [22] observed that fly ash soiling during heating seasons reduces the availability of power by up to 30% in urban PV systems. Reliability estimation and additional DC voltage limitations are important for maintaining uninterrupted hybrid microgrid operations. Liu *et al*. [23] focused on improving daily maintenance planning for PV power plants by considering time-varying output power to minimize costs. Reduced costs were compared with traditional methods after developing a mixed-integer linear programming model and a heuristic algorithm. Pimpalkar *et al*. [24] identified crucial problems like overloading, current leakage, earthing wire faults, and grounding problems by using Failure Modes and Effects Analysis (FMEA). Sonawane *et al*. [25] found fuzzy theory-based FTA approach to finding the failure probabilities of the faults is more effective compared to traditional FTA. Through this approach, soiling, poor maintenance, and improper installation are found to be the common issues that affect the performance and reliability of solar PV systems. Orosz *et al*. [26] emphasized the difficulties involved in operating and maintaining solar power plants in the EU, where production depends heavily on weather. Fitrianingtyas *et al*. [27] analyzed the reliability, maintainability, and availability of 48V solar panels of a hybrid power plant in Pantai Baru using Weibull distribution. It is observed that predictive modeling techniques are very less opted for performance prediction of solar photovoltaic power plants under the concept of redundancy.

Patil *et al*. [28] used Failure Mode and Effects Analysis (FMEA) to identify the most critical part and focused on improving the reliability and risk management of polycrystalline solar PV panels. In parallel, machine learning algorithms and prediction tools showed applicability in several domains. Odekina *et al*. [29] used prediction techniques in forecasting the third wave of Covid-19 incidence rate. Ibidoja *et al*. [30] used robust M-estimators and machine learning algorithms for improving the predictive accuracy of seaweed contaminated big data. Hassan and Ismail [31] used quantile regression neural network combined with unrestricted mixed data sampling to improve the accuracy. Obini *et al*. [32] developed a machine learning based fileless malware filter system for cyber-security. In the shift towards sustainable energy solutions, solar PV power plants are becoming more important. However, their system failures and maintenance strategies can affect their performance. To optimize their efficiency and dependability, high availability must be ensured. The need for precise predictive models that can increase the availability of solar PV plants with better maintenance strategies and effective design is the only motive of this research.

Hence, an investigation is performed to develop an efficient mathematical model for the prediction of the system availability of a solar photovoltaic power plant under the concept of redundancy and exponentially distributed random variables. A stochastic model is formed for this idea with the Markov birth-death technique due to the constant behavior of failure and repair rates of the solar PV plants observed from various studies as cited in the literature. It is assumed that all the repairs are ideal and that random variables are statistically independent. The predictive techniques of regression modeling and artificial neural networks are used for the prediction of the availability of the PV power plant in different experimental setups with the help of SPSS. The effects on the availability by failure and repair rates of PV solar power plants are noted. The Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) of both predictive techniques derived with the help of experimental data. It is identified that the MAE and RMSE of the regression model are less in comparison to the ANN model. So, the regression model outperforms ANN in the performance prediction of PV power plants. The findings of this research have useful implications for scientists, engineering, and researchers. The main goal of this research is to develop an effective and accurate mathematical model to predict the availability of solar PV plants. The outcomes of this study may help design PV solar plants and plan maintenance strategies for solar PV power plants. This study can also determine a useful framework for industrial applications to develop wider and for future evaluation with hybrid models.

The organization of this paper contains a total of five sections. Section 1 contains an introduction, section **??** contains material and methods, section 3 contains a stochastic model of solar PV power plant, section 4 contains predictive modeling and numerical results, and section 5 concludes the paper by providing some benefits of the proposed method.

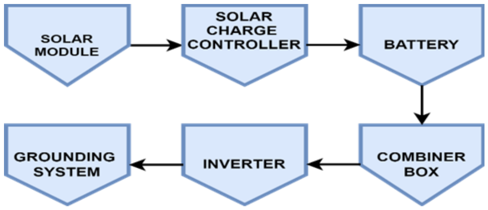

Figure 1: Flowchart of PV solar plant

2. Material and methods

2.1. System description

The photovoltaic solar power plant system constitutes six subsystems namely: solar module, solar charge controller, battery, combiner box, inverter, and grounding system. All the subsystems are arranged in a series configuration. The flow chart of the PV system is appended in Figure 1 and Table 1 contains failure and repair rates of subsystems.
Below is the brief description of each subsystem:

1. *Subsystem A (Solar Module):* Conversion of sunlight into electricity is performed by this subsystem. It consists of four solar modules configured as a 3-out-of-4: G structure. Complete system failure is caused by the failure of more than one unit.
2. *Subsystem B (Solar Charge Controller):* Electricity flow between module, battery, and loads is controlled by this subsystem. It consists of only one unit. It is connected in series with battery. Due to its failure, complete system fails.
3. *Subsystem C (Battery):* Energy generated by solar panels is stored in this subsystem. It involves three units configured as a 2-out-of-3: G system. Complete system failure is caused by failure of more than one unit.
4. *Subsystem D (Combiner Box):* It is used to combine the output of multiple solar strings. It consists of single unit and connects in series with inverter. Due to its failure, complete system fails.
5. *Subsystem E (Inverter):* It is used to convert direct current produced by solar panel into alternate current. It consists of only one unit. Due to its failure, complete system fails.
6. *Subsystem F (Grounding System):* It protects the PV system from over voltage, lighting strikes, and transient voltage surges. It consists of only one unit. Due to its failure, complete system fails.

2.2. Artificial neural network

Initiation of neural networks observed between 1950-1970. Several researchers developed ANN models for prediction of various phenomena. Zou *et al*. (2009) proposed a modified artificial neural network (ANN) model as a machine learning method developed from the concept of brain simulation. Artificial neural networks work based on the behaviour of biological neural networks. It is an interconnection of nodes, analogous to neurons. Each neural network has three important components: Node character, Network topology, and Learning rules.

Table 1: Photovoltaic solar power plant's failure and repair rates.

S. No.	Components	Failure rate $(\lambda_i)h^{-1}$	Repair rate $(\mu_i)h^{-1}$
1	Solar Module (L)	0.001	0.5
2	Solar Charge Controller (M)	0.002	0.7
3	Battery (N)	0.003	0.9
4	Combiner Box (O)	0.0053	1.124
5	Inverter (P)	0.004	1.1
6	Grounding System (Q)	0.005	1.3

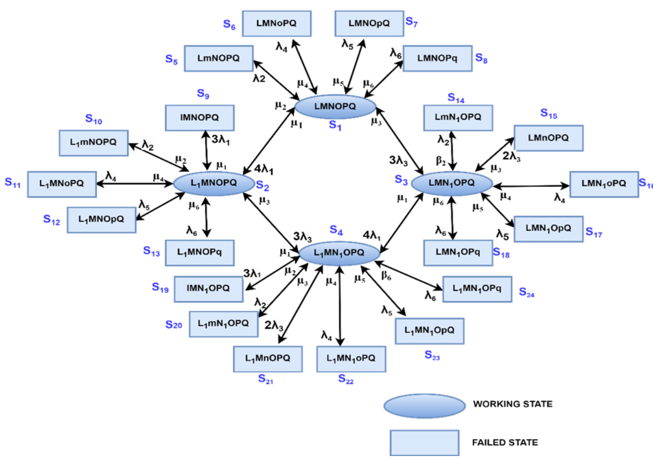

Figure 2: State transition diagram of PV power plant.

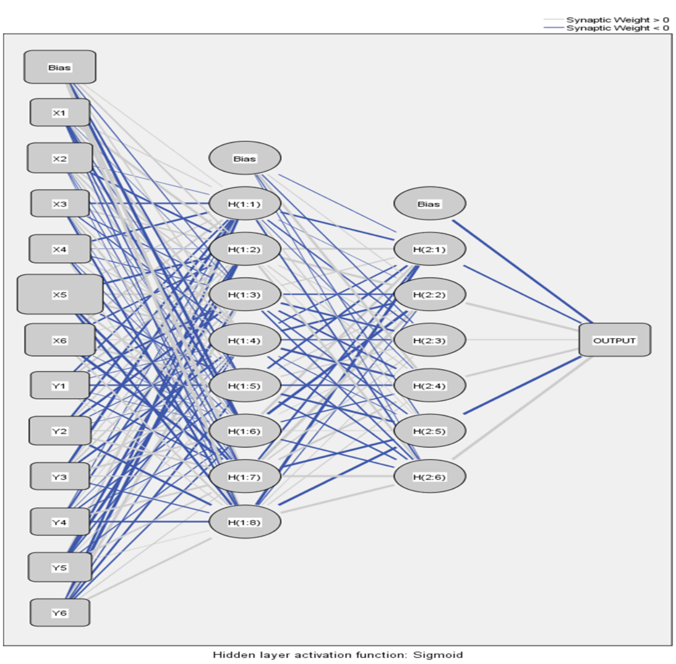

Figure 3: Network structure for ANN.

Node character, network topology, and learning rules are the

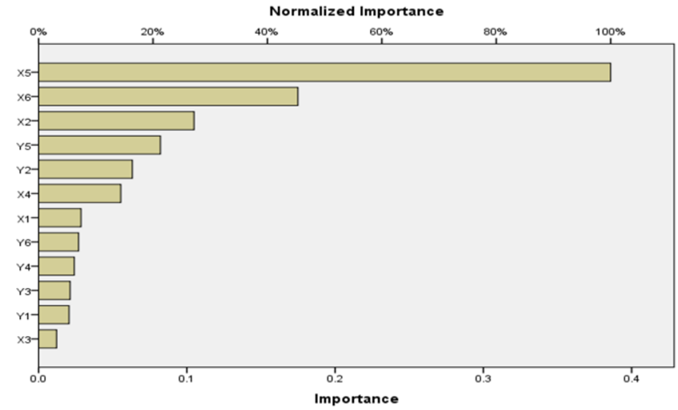

Figure 4: Rank as well as normalized rank of twelve variables.

three critical components of each neural network. How signals are processed by the node is determined by the node character, such as the number of inputs and outputs associated with the node, the weight associated with each input and output, and the activation function. The organization and connection of nodes are determined by network topology. How the weights are initialized and adjusted is determined by learning rules. In this study, we used a special type of artificial neural network (feed-forward neural network). It is also known as multi-layer perceptron (MLP), a fundamental type of artificial neural network. It is a class of artificial neural networks in which information flows in one direction, from the input layer to the output layer, without forming cycles.

2.3. Multiple linear regression

A strong statistical technique, multiple linear regression, analyses the relationship between predictors (multiple input parameters) and response (dependent variable). This method is used to find out the variation of the model and the contribution of each independent variable to the total variation. It consists of two types: linear regression and non-linear regression. It models the dependent variable as a linear combination of independent variables. Its expression is written as $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon$, where $X_1, X_2, \ldots, X_n$ are predictors, Y is the response, β represents coefficients, and ϵ is the error term. It is used to understand the complex relationship between variables and is used in fields like biology, social science, and economics.

2.4. Mean absolute error

The Mean Absolute Error (MAE) estimates the mean size or the average magnitude between the predicted and observed values.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |P_i - O_i|, \quad (1)$$

where P_i represents the predicted value or O_i denotes the observed value, and n is the total number of data points.

Table 2: PV plant output availability data.

λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	μ_1	μ_2	μ_3	μ_4	μ_5	μ_6	Proposed model availability	Predicted availability by regression	Predicted availability by ANN
0.002	0.002	0.003	0.0053	0.004	0.005	0.5	0.7	0.9	1.124	1.1	1.3	0.984921	0.98464	0.9847611716
0.0022	0.002	0.003	0.0053	0.004	0.005	0.5	0.7	0.9	1.124	1.1	1.3	0.984883	0.98459	0.9847329535
0.0024	0.002	0.003	0.0053	0.004	0.005	0.5	0.7	0.9	1.124	1.1	1.3	0.984842	0.98454	0.9847008971
0.0026	0.002	0.003	0.0053	0.004	0.005	0.5	0.7	0.9	1.124	1.1	1.3	0.984798	0.98449	0.9846650091
0.0028	0.002	0.003	0.0053	0.004	0.005	0.5	0.7	0.9	1.124	1.1	1.3	0.98475	0.98445	0.9846253178
0.003	0.002	0.003	0.0053	0.004	0.005	0.5	0.7	0.9	1.124	1.1	1.3	0.984698	0.98440	0.9845818721
0.0032	0.002	0.003	0.0053	0.004	0.005	0.5	0.7	0.9	1.124	1.1	1.3	0.984643	0.98435	0.9845347389
0.0034	0.002	0.003	0.0053	0.004	0.005	0.5	0.7	0.9	1.124	1.1	1.3	0.984585	0.98430	0.9844840017
0.0036	0.002	0.003	0.0053	0.004	0.005	0.5	0.7	0.9	1.124	1.1	1.3	0.984524	0.98425	0.9844297585
0.0038	0.002	0.003	0.0053	0.004	0.005	0.5	0.7	0.9	1.124	1.1	1.3	0.98446	0.98420	0.9843721195
0.004	0.002	0.003	0.0053	0.004	0.005	0.5	0.7	0.9	1.124	1.1	1.3	0.984392	0.98415	0.9843112058
0.0042	0.002	0.003	0.0053	0.004	0.005	0.5	0.7	0.9	1.124	1.1	1.3	0.984321	0.98410	0.9842471471
0.0044	0.002	0.003	0.0053	0.004	0.005	0.5	0.7	0.9	1.124	1.1	1.3	0.984247	0.98406	0.9841800802
0.0046	0.002	0.003	0.0053	0.004	0.005	0.5	0.7	0.9	1.124	1.1	1.3	0.98417	0.98401	0.9841101475
0.0048	0.002	0.003	0.0053	0.004	0.005	0.5	0.7	0.9	1.124	1.1	1.3	0.98409	0.98396	0.9840374952
0.005	0.002	0.003	0.0053	0.004	0.005	0.5	0.7	0.9	1.124	1.1	1.3	0.98401	0.98391	0.9839622725

Table 3: Proposed multiple regression summary.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
Proposed	0.859	0.739	0.728	0.0020409898523

Table 4: Testing of the regression model.

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	0.003	12	0.000	67.551	<0.001
Residual	0.001	287	0.000		
Total	0.005	299			

2.5. Root mean square error

The Root Mean Square Error (RMSE) calculates the square root of the average of the squared differences between the predicted and observed values.

$$RMSE = \sqrt{\left[\left(\frac{1}{n}\right)\sum_{i=1}^{n}(P_i - O_i)^2\right]}. \tag{2}$$

3. Stochastic model of solar power plant

The availability is a key metric to identify the most sensitive component of PV power plants. The plant's operation is significantly influenced by the frequency of component failures and the speed of repairs. In this section, a stochastic model is formed using the Markovian birth-death technique to predict the availability of PV power plants using various predictive analysis techniques. By considering the probability that at time 't' system is at state. The differential-difference equation of the system is derived with the help of the state transition diagram given in Figure 2.

The differential-difference equations are derived as follows:

$$(4\lambda_1 + \lambda_2 + 3\lambda_3 + \lambda_4 + \lambda_5 + \lambda_6)P_1 = \mu_1 P_2 + \mu_2 P_5 + \mu_3 P_3 + \mu_4 P_6 + \mu_5 P_7 + \mu_6 P_8, \tag{3}$$

$$(3\lambda_1 + \lambda_2 + 3\lambda_3 + \lambda_4 + \lambda_5 + \lambda_6 + \mu_1)P_1 = \mu_1 P_9 + \mu_2 P_{10} + \mu_3 P_4 + \mu_4 P_{11} + \mu_5 P_{12} + \mu_6 P_{13} + 4\lambda_1 P_1, \tag{4}$$

$$(4\lambda_1 + \lambda_2 + \lambda\alpha_3 + \lambda_4 + \lambda_5 + \lambda_6 + \lambda_3)P_1 = \mu_1 P_4 + \mu_2 P_{14} + \mu_3 P_{15} + \mu_4 P_{16} + \mu_5 P_{17} + \mu_6 P_{18} + 3\lambda_3 P_1, \tag{5}$$

$$(3\lambda_1 + \lambda_2 + 2\lambda_3 + \lambda_4 + \lambda_5 + \lambda_6 + \lambda_3 + \mu_1)P_1 = \mu_1 P_{19} + \mu_{20} + \mu_3 P_{21} + \mu_4 P_{22} + \mu_5 P_{23} + \mu_6 P_{24} + 3\mu_3 P_2 + 4\lambda_1 P_3, \tag{6}$$

$$\lambda_2 P_1 = \mu_2 P_5, \tag{7}$$

$$\sum_{a=4}^{6} \lambda_a P_1 = \sum_{b=4}^{6} \mu_b P_{b+2}, \tag{8}$$

$$3\lambda_1 P_2 = \mu_1 P_9, \tag{9}$$

$$\lambda_2 P_2 = \mu_2 P_{10}, \tag{10}$$

$$\sum_{c=4}^{6} \lambda_c P_2 = \sum_{d=4}^{6} \mu_d P_{d+7}, \tag{11}$$

$$\lambda_2 P_3 = \mu_2 P_{14}, \tag{12}$$

$$2\lambda_3 P_3 = \mu_3 P_{15},, \tag{13}$$

$$\sum_{e=4}^{6} \lambda_e P_3 = \sum_{f=4}^{6} \mu_f P_{f+12}, \tag{14}$$

$$3\lambda_1 P_4 = \mu_1 P_{19}, \tag{15}$$

$$\lambda_2 P_4 = \mu_2 P_{20}, \tag{16}$$

$$2\lambda_3 P_4 = \mu_3 P_{21}, \tag{17}$$

$$\sum_{g=4}^{6} \lambda_g P_4 = \sum_{h=4}^{6} \mu_h P_{h+18}\,. \tag{18}$$

Initial conditions are

$$P_i(0) = \begin{cases} 1, & \text{if } i = 0, \\ 0, & \text{if } i \neq 0. \end{cases} \tag{19}$$

By using initial conditions in equation (19) and normalization condition, that is $\sum_{i=1}^{24} P_i = 1$, we solve the above system of

Table 5: Multiple regression analysis of PV solar power plant.

	Unstandardized Coefficients		Standardized Coefficients			Collinearity	95% of CI for independent variables	
Model	β	Std. Error	Beta	t	Sig.	VIF	Lower Bound	Upper Bound
Constant	0.983	0.018		54.044	0.000		0.947	1.019
λ_1	-0.244	0.116	-0.067	-2.106	0.036	1.124	-0.472	-0.016
λ_2	-1.322	0.179	-0.234	-7.404	0.000	1.097	-1.674	-0.971
λ_3	0.058	0.116	0.016	0.500	0.617	1.124	-0.170	0.286
λ_4	-0.715	0.168	-0.135	-4.266	0.000	1.096	-1.045	-0.385
λ_5	-0.854	0.035	-0.756	-24.127	0.000	1.077	-0.924	-0.785
λ_6	-0.724	0.077	-0.293	-9.357	0.000	1.079	-0.877	-0.572
μ_1	0.001	0.002	0.021	0.677	0.499	1.106	-0.002	0.004
μ_2	0.001	0.000	0.092	2.960	0.003	1.069	0.000	0.002
μ_3	0.000	0.001	0.012	0.370	0.712	1.078	-0.001	0.001
μ_4	0.009	0.015	0.019	0.605	0.546	1.110	-0.020	0.038
μ_5	0.001	0.000	0.147	4.666	0.000	1.090	0.001	0.001
μ_6	0.002	0.002	0.031	0.997	0.320	1.094	-0.002	0.006

Table 6: Network information of ANN.

Input Layer	Covariates	1	X1 Failure rate (λ_1)
		2	X2 Failure rate (λ_2)
		3	X3 Failure rate (λ_3)
		4	X4 Failure rate (λ_4)
		5	X5 Failure rate (λ_5)
		6	X6 Failure rate (λ_6)
		7	Y1 Repair rate (μ_1)
		8	Y2 Repair rate (μ_2)
		9	Y3 Repair rate (μ_3)
		10	Y4 Repair rate (μ_4)
		11	Y5 Repair rate (μ_5)
		12	Y6 Repair rate (μ_6)
	Number of Units[a]		12
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		2
	Number of Units in Hidden Layer 1[a]		8
	Number of Units in Hidden Layer 2[a]		6
	Activation Function		Sigmoid
Output Layer	Dependent Variables	1	OUTPUT
	Number of Units		1
	Rescaling Method for Scale Dependents		Normalized
	Activation Function		Sigmoid
	Error Function		Sum of Squares

equations from (3)-(18), and get the expression for P_1 as given below,

$$P_1 = \left[\left(1+\frac{\lambda_2}{\mu_2}+\frac{\lambda_4}{\mu_4}+\frac{\lambda_5}{\mu_5}+\frac{\lambda_6}{\mu_6}\right)(1+A+B+C) + \left(\frac{3\lambda_1}{\mu_1}+\frac{2\lambda_3}{\mu_3}\right)A + \left(\frac{2\lambda_3}{\mu_3}\right)B + \left(\frac{3\lambda_1}{\mu_1}\right)C\right]^{-1}, \tag{20}$$

where

$$A = \frac{[a_1+a_2]}{[\mu_1+\mu_3-a_3-a_4]},\quad B = \left[\frac{\mu_1 A + 3\lambda_3}{4\lambda_1+\mu_3}\right],\quad C = \left[\frac{4\lambda_1+\mu_1 A}{3\lambda_1+\mu_1}\right],$$

$$a_1 = \left[\frac{12\lambda_1\lambda_3}{3\lambda_3+\mu_1}\right],\quad a_2 = \left[\frac{12\lambda_1\lambda_3}{4\lambda_1+\mu_3}\right],\quad a_3 = \left[\frac{3\lambda_3\mu_3}{3\lambda_3+\mu_1}\right],\quad a_4 = \left[\frac{4\lambda_1\mu_1}{4\lambda_1+\mu_3}\right]. \tag{21}$$

The steady state availability of

$$A_0 = P_1+P_2+P_3+P_4 = \frac{1+A+B+C}{\left[\left(1+\frac{\lambda_2}{\mu_2}+\frac{\lambda_4}{\mu_4}+\frac{\lambda_5}{\mu_5}+\frac{\lambda_6}{\mu_6}\right)(1+A+B+C) + \left(\frac{3\lambda_1}{\mu_1}+\frac{2\lambda_3}{\mu_3}\right)A + \left(\frac{2\lambda_3}{\mu_3}\right)B + \left(\frac{3\lambda_1}{\mu_1}\right)C\right]}. \tag{22}$$

Table 7: Parameter estimation for availability of solar power plant.

		Predicted														
		Hidden Layer 1								Hidden Layer 2						Output Layer
Predictor		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	H(1:6)	H(1:7)	H(1:8)	H(2:1)	H(2:2)	H(2:3)	H(2:4)	H(2:5)	H(2:6)	OUTPUT
Input Layer	(Bias)	0.068	0.285	-0.130	0.209	-0.306	-0.508	0.665	0.517							
	X_1	0.168	0.488	-0.009	0.415	-0.091	-0.393	-0.200	-0.162							
	X_2	-0.052	-0.396	0.305	0.312	0.215	-0.021	-0.074	-0.015							
	X_3	-0.413	0.381	-0.201	-0.228	0.187	0.377	-0.003	-0.350							
	X_4	-0.438	-0.041	-0.159	0.241	0.116	-0.052	-0.286	0.126							
	X_5	0.245	-0.509	0.463	0.536	-0.333	0.409	-0.473	-0.418							
	X_6	0.387	-0.335	0.084	0.179	0.489	-0.019	-0.538	0.335							
	Y_1	-0.307	0.378	-0.427	-0.086	-0.358	-0.024	-0.297	0.120							
	Y_2	-0.399	0.232	-0.428	-0.131	-0.017	0.383	0.454	-0.466							
	Y_3	-0.485	0.175	0.314	-0.391	0.340	0.471	0.267	-0.255							
	Y_4	-0.081	-0.295	0.062	-0.037	-0.279	-0.152	0.433	-0.426							
	Y_5	0.354	-0.410	-0.495	-0.234	0.071	-0.156	0.359	0.055							
	Y_6	-0.424	-0.633	0.511	-0.182	-0.357	-0.271	0.135	0.432							
Hidden Layer 1	(Bias)									-0.116	0.102	-0.167	0.451	-0.124	-0.047	
	H(1:1)									-0.402	-0.016	-0.256	-0.072	0.156	-0.279	
	H(1:2)									0.457	0.662	0.124	0.171	0.017	0.417	
	H(1:3)									0.260	-0.342	-0.435	-0.385	-0.260	-0.277	
	H(1:4)									-0.286	-0.466	-0.315	-0.541	-0.111	-0.287	
	H(1:5)									-0.395	0336	0.288	-0.382	-0.480	-0.334	
	H(1:6)									0.459	-0.609	0.065	-0.268	0.072	-0.317	
	H(1:7)									-0.335	1.054	0.231	0.445	-0.498	0.652	
	H(1:8)									-0.516	-0.131	0.069	0.146	-0.156	0.613	
Hidden Layer 2	(Bias)															-0.480
	H(2:1)															-0.338
	H(2:2)															1.089
	H(2:3)															0.217
	H(2:4)															0.539
	H(2:5)															-0.566
	H(2:6)															0.780

4. Predictive modeling and numerical results

In this part, initially, the steady state availability of the proposed model is derived with respect to the failure rate having arbitrary values of the parameters given in Table 1. It is found that steady state availability of the PV system decreases with the increase of the failure rate. Later, multilayer feed-forward Neural Networks and Multiple Linear Regression techniques were applied to predict the availability of PV plants on the sample observation generated through the projected model. The failure rates and repair rates of all six subsystems are termed predictors while availability is the response variable. A sample of 300 observations is generated and predictive modeling implementation is done in SPSS software. The goodness-of-fit and model accuracy measures like MAE and RMSE are derived to compare the performance of the Multi-layer Feed-Forward Neural Network (MLFFNN) and Multi Linear Regression (MLR) models. An extract of sample data is shown in Table 2 along with the predicted values derived from the MLFFNN and MLR models.

4.1. Multi linear regression (MLR)

The theories of classical Multiple Linear Regression were checked on the experimental data and it was observed that no multicollinearity, autocorrelation, and heteroscedasticity were present in the data. The classical linear regression model is applied to develop a regression model using SPSS. It is observed from Table 3 that, the value of the proposed model is 0.739 and adjusted is 0.728 respectively having a standard error of 0.00204. Table 4 shows the results of the ANOVA test for the given regression model's statistical significance, from which it was found that the p-value (<0.0001) is less than the level of significance. From Table 5, it is found that the VIF index is less than 10 which reflects that there is no multicollinearity present in the data. The developed model is statistically significant to calculate the availability of the PV solar power plant. The other goodness-of-fit measures like RMSE and MAE were also derived using equations (1)-(2) as 0.00199624815 and 0.000377603333.

4.2. Multi-layer feed-forward neural network (MLFFNN)

For availability prediction of solar power MLFFNN model is formed. The specified data of 300 observations is divided into the ratio of 68.7% and 31.3% for training and testing respectively. As shown in Figure 3, the MLFFNN model for availability prediction consists of four layers viz. input layer, two hidden layers, and an output layer. In the neural network, there are twelve covariates in the input layer, eight neurons in the first hidden layer, and six neurons in the second hidden layer. As shown in Table 6, the standardized technique is used to rescale the covariates with "sigmoid" used as the activation function and the normalized method with "sigmoid" used as the activation function and "sum of squares" used as the error function for rescaling the dependent variables. Parameter estimation values of input as well as hidden layers are shown in Table 7. It is revealed from Table 8 and Figure 4 that failure rate ($\lambda 5$) is most important in the availability prediction of the solar power plant. The goodness-of-fit measures RMSE and MAE of the ANN model are derived as 0.00208400416 and 0.000504586667 respectively.

5. Conclusion

This study tries to establish a precise model for forecasting the availability of the solar power plant. A stochastic model is developed by using exponential distribution for failure and repair rates, from which availability results for a specific case are derived. From numerical results, it is found that availability of the solar power plants decreases with an increase in the failure rate. For the proposed model, the predicted values also show the same pattern concerning the failure rates. The RMSE and MAE of Multiple Linear Regression model are found to be lesser than the MLFFNN. Therefore, MLR outperforms MLFFNN. For planning the strategies and maintenance of the solar power plant, the multiple linear regression model can be utilized for availability estimation. However, the proposed methodology is suggested for systems having exponential behaviour of failure and repair rates. For arbitrarily distributed behaviour separate investigation is required. For the industries of types, the suggested methodology can be used for availability prediction. Further, the work can be explored in the future by using hybrid models that combine regression with other machine-learning techniques under various assumptions.

Data availability

The data will be available on request from the corresponding author.

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