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Performance Assessment of Solar-Transformer-Consumption System Using Neural Network Approach

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Abstract:

Solar energy is one of the immeasurable renewable energy in power generation for a green, clean and healthier environment. The silicon-layer solar panels absorb sun energy and converts it into electricity by off-grid inverter. Electricity is transferred either from this inverter or from transformer, consumed by consumption unit(s) available for residential or economic purposes. The artificial neural network is the foundation of artificial intelligence and solves many complex problems which are difficult by statistical methods or by humans. In view of this, the purpose of this work is to assess the performance of the Solar - Transformer - Consumption (STC) system. The system may be in complete breakdown situation due to failure of both solar power automation subsystem and transformer simultaneously or consumption unit; otherwise it works with fully or lesser efficiency. Statistically independent failures and repairs are considered. Using the elementary probabilities phenomenon incorporated with differential equations is employed to examine the system reliability, for repairable and non-repairable system, and to analyze its cost function. The accuracy and consistency of the system can be improved by feed forward- back propagation neural network (FFBPNN) approach. Its gradient descent learning mechanism can update the neural weights and hence the results up to the desired accuracy in each iteration, and aside the problem of vanishing gradient in other neural networks, that increasing the efficiency of the system in real time. MATLAB code for FFBP algorithm is built to improve the values of reliability and cost function by minimizing the error up to 0.0001 precision. Numerical illustrations are considered with their data tables and graphs, to demonstrate and analyze the results in the form of reliability and cost function, which may be helpful for system analyzers.

Keywords: Cost function, Feed forward-back propagation neural network algorithm, Gradient descent optimization method, Reliability.

Introduction:

In today's scenario, demand of electricity is more than its generation. As known, conventional resources such as fossil fuels, coal, nuclear, natural gases, etc. are decreasing day- by - day due to increase in their consumption in various activities of human beings. To reduce the dependency on conventional / non-renewable energy, it is necessary to promote the use of renewable energy. Water (hydro), Wind, Geothermal, Biomass and Solar energy are considered as renewable energy resources. They can replenish themselves to restore the part, depleted by human activities. The construction of hydro power plant, wind parks, geothermal energy plant, biomass plants are very expensive and establishing far away from human habitat. Thus, construction cost of these plants and electricity transportation from power plant to consumer place are too high.

On the other hand, the solar-powered photovoltaic modules made up of silicon cell layers, metallic frame, glass casing units and wires that absorb solar energy and generate electric current. Solar panels can be installed according to its main three scopes: Residential-scope (on rooftops/ land area of houses and provide electricity to a particular house), Commercial-scope (for business/ economic purpose and non-profitable), Utility-scope (on the central area to provide electricity to a large number of customers). Thus, solar power plant needs large space to assemble only for business purpose, whereas on the other hand it can be easily incorporated on rooftop of houses. Solar energy reduces pollution, global warming, green-house effect etc..

Also, International Energy Agency quotes that 26% of the world's electricity only depends on renewable energy resources and is expected to achieve 30% by 2024. As the tremendous advantages of renewable energy resources viz. lower maintenance cost, health and environmentally friendly, less dependent on import of energy, replenish timely over the nonrenewable energy, the world is evolving to sustainable energy and a sustainable future.

From all this, solar energy is the only renewable energy available from large scale to small scale and approachable for residential area [1-4]. The authors considered residential solar-power-plant system incorporated with transformer electricity, to generate electricity and that can easily assemble on the roof top of houses. Considered system consists of three main subsystems viz. *Solar power automation subsystem* comprises Solar panels, off grid inverter, system monitoring unit, Battery bank: electricity from *Transformer subsystem* to our houses and *Consumption unit,* as shown in Fig. 1. The prime objective of this work is to study a reliable, economic, and quality rich system.

When the word 'reliable' was inculcated with hardware, software or theory of these, it acknowledged by 'reliability'. During World War II, the word 'reliability' acclaimed for analyzing the missiles. After that reliability leaves an impression on every device to improve the quality of individual component or whole product. As the development continues, complexity of devices increased with the demand of more reliable product [5-7]. A remarkable progress has been recognized in the domain of equipment, complex system, industries, and organizations. To estimate the reliability, failure measures of component(s) need to be evaluated. According to theory of reliability, multi-component system can be evolved into mathematical models either in probabilistic or integro-differential equations, by choosing suitable design parameters such as deficiencies, breakdown(s), and recovery of the system [8-9]. One can work out on these equations for analyzing reliability, cost, system availability and the parameters from which system is more effective using well known techniques such as fault tolerant tree, stochastic reward nets, Petri nets, Monte Carlo introducing supplementary variable, copula method, regenerative point method etc. [10]. All these and many more methods are sufficient to evaluate the different reliability parameters but inefficient to improve the existing result and update the failures and repairs [11]. Many authors discussed the failures and recovery modes of components and hence system performance [12]. System has been analyzed with its reliability and mean time to system failure that may be increased with increasing the number of components in its subsystem [13-14].

Recent era involves many soft computing techniques such as fuzzy logic theory (inputs depend upon dependency/ interdependency of variables), neural network approach (when the desired output is known and calculated output is improved to desired extent) , evolutionary genetic algorithm etc. to establish the level of results [15-16]. Out of these techniques, neural networks approach, inspired by the biological neurons system of humans, is extensively incorporated with solving and improving the results of problems related to complex engineering structures. Basically, neural network architecture are considered, depends on their components; namely; set of neurons, connected network and learning / training mechanism. Learning mechanisms are mainly derived by Supervised, Unsupervised and Reinforced learning mechanism. In *Supervised learning*, the system is trained using well defined set of input and output data that is based on previous experience(s).To improve the performance of the system, gap can be evaluated between computed and desired output. In *Unsupervised learning*, the system is trained using input data along with structured features of self-learning while target output is not present with the network. Different from these, in *Reinforced learning*, only learning process with reward or penalty is provided to the network that depends on correct or incorrect actions performed. Besides with learning mechanism, structure of interconnected network(s) includes the following architecture:

- Single layer feed forward architecture comprises of two layers, input and output, connected by synaptic links that carries the weights. Only output layer computes the result, hence its name is single layer.
- Multilayer feed forward architecture incorporate with multiple layers; input, hidden and output; connected by weighted synaptic links. Hidden layer neurons also perform computation before output layer and refine the results. It follows bidirectional propagation i.e. firstly forward and then backward to reduce the error and optimize the results.
- Recurrent architecture consists of input, hidden and output layer connected by weighted

synaptic links with at least one self-feedback loop, that fed back the output/ variance in output into itself as input. It also performs bidirectional propagation i.e. firstly feed forward followed by recurrent loop. If evaluated result is not up to desired output, the learning mechanism is employed to make changes and move towards the right prediction during back propagation. It stores information as gradient for future amendments. But if initial gradient is small, the upgradation of weights in further layers will be smaller, that arises the problem of vanishing gradients. Due to which, the network fails to train, reducing the error and optimize the results.

Keeping all these facts in mind, authors give the priority to neural network multilayered arrangement consists of three main layers: input, hidden and output. These layers are associated with synaptic links that assimilate the weights and learning algorithm to govern the system. A well-connected set of neurons and learning mechanism describe the process of adjusting/ updating the weights to desired accuracy and minimize the errors in each iteration using feed forward back propagation neural network (FFBPNN) structure and gradient descent algorithm. It was formerly proposed in 1970s for training the system and minimizing the errors appropriate for required precision. Some analysts have applied the evolutionary algorithm on multi-objective optimization problem to evaluate reliability of redundant components. The researchers obtained a novel NN, the variable weights, which determine enormous ability to cope with complicated recognition and classification problems [17-18].

The stand-alone photovoltaic residential generation system studied the uncertainties of solar radiation due to environmental conditions with component failures [19]. Monte Carlo Simulation Method is used to evaluate the application of solar panels in a vigorous manner [20]. Analysts recapitulated the availability, existing status, promotion policies and future possibilities of different forms of solar energy [21-23]. Some researchers make it multipurpose and more beneficial for the masses latest inclinations and innovations. To enhance the clean and green energy, they proposed that solar power plants may be installed in such a way that they work in accord with hydro and methods of power generation. The authors discussed the working, and types of solar panels. They highlighted the various applications and methods to endorse the benefits of solar energy, as compared to other forms of conventional energy [24].

This paper is designed to assess the reliability parameters and effective cost of Solar-Transformer-Consumption unit ($\mathcal{STC}$) system and optimize the results up to desired extent using learning mechanism of FFBPNN.

System Description:

Firstly, French physicist Edmond Becquerel discovered the science of generating electricity with solar panels in 1839. Afterwards, Willoughby Smith (1873), William Grylls Adams and Richard Evans Day (1876), American inventor Charles Fritz (1883) and many more worked on Becquerel selenium solar cell. In 1905, Albert Einstein derived the solar energy potential on broader scale. Daryl Chapin, Calvin Fuller, and Gerald Pearson, firstly, developed silicon photovoltaic cell at Bell laboratory in 1954. By which, solar energy was captured and converted into usable source of electricity. At the beginning, conversion of solar energy into electricity was a slow process as well as the cost was too high. Subsequently, design of solar panels, number of states, federal incentives and policies driven down the cost that is easily available at residential scope as well. For residential scope, the authors examined the Solar-Transformer-Consumption ($\mathcal{STC}$) system, consists of following subsystems:

1. **Subsystem $\mathcal{S}$** - *Solar power automation*: It comprised solar panels, off grid inverter, system monitoring unit and Battery bank. The solar panels absorb light from sun and change that energy to DC (Direct Current). The off-grid inverter converts DC to AC and stores it into battery bank. The system monitoring unit administers the power, voltage and current of the system.
2. **Subsystem $\mathcal{T}$** - *Transformer:* It connects with electricity power grid, commonly named hydel, and regulates electricity from consumption places to our residence or business.
3. **Subsystem $\mathcal{C}$** - *Consumption unit:* Consumption unit or load where the whole electricity is being used for different purposes.

All the units of subsystem S are interconnected and work with reduced efficiency due to failure of off -grid inverter and battery bank if subsystem $\mathcal{T}$ works well. At this moment, if subsystem $\mathcal{T}$ fails, the system will fail completely. Similarly, if subsystem $\mathcal{T}$ may fail first then system reduces its works efficiency and after that, may fails due to failure of off -grid inverter and battery bank. That means, the complete system may fail due to failure of both subsystem $\mathcal{S}$ and $\mathcal{T}$ simultaneously. Failures of some of the solar panel(s) or monitoring unit reduce the efficiency of the system from either

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of the system state. Failure of subsystem C becomes the cause of complete failure of system from any of the system state. Figure 1 depicts the $\mathcal{STC}$ system layout and all its perspectives considered by authors are shown in Fig. 2, in the form of transition state diagram. Following conditions for working of the system are assumed:

1. In the beginning, all subsystems/ units are in completely operable position, so is the system.
2. The system is in degraded state if any solar panel or monitoring unit of subsystem S fails from any of the state.
3. The system may face complete break down due to failure of both subsystem S and T simultaneously
4. The system is also in complete failed state due to failure of subsystem C from any state.
5. System States are interconnected by failures and repairs, as shown in Fig. 2.
6. Repairs and failures are statistically independent.
7. Remaining units/ subsystem cannot fail from failed state.
8. Repair facility is available at every state, either directly or from degraded state.
9. After repair, subsystem/ units/ system work as normal.
10. On considering FFBPNN technique, all failures and repairs are established as synaptic neural weights.

Notations and Definitions:

η_B	Constant failure when battery bank out of service
η_I	Constant failure when off-grid inverter out of service
η_T	Constant failure when transformer out of service
η_M	Constant failure when monitoring unit is not working
η_P	Constant failure when some solar panel(s) is not working
η	Constant failure when multiple units out of service simultaneously
η_C	Constant failure when consumption unit out of service
ξ	Constant repair when subsystem / unit repaired after facing failure
D	$\frac{d}{dt}$
$P_i(t)$	i^{th} system state probability at any time t, i= 1, 2, . . . , 9
$P_i(t + \Delta t)$	i^{th} system state probability at time $t + \Delta t$, i= 1, 2, . . . , 9

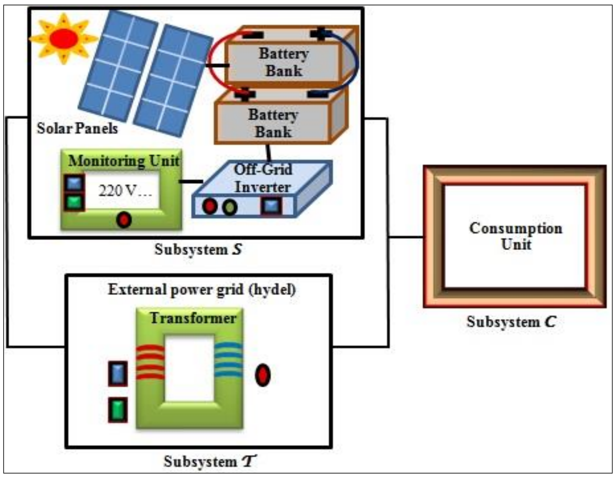

Figure 1. $\mathcal{STC}$ system Layout

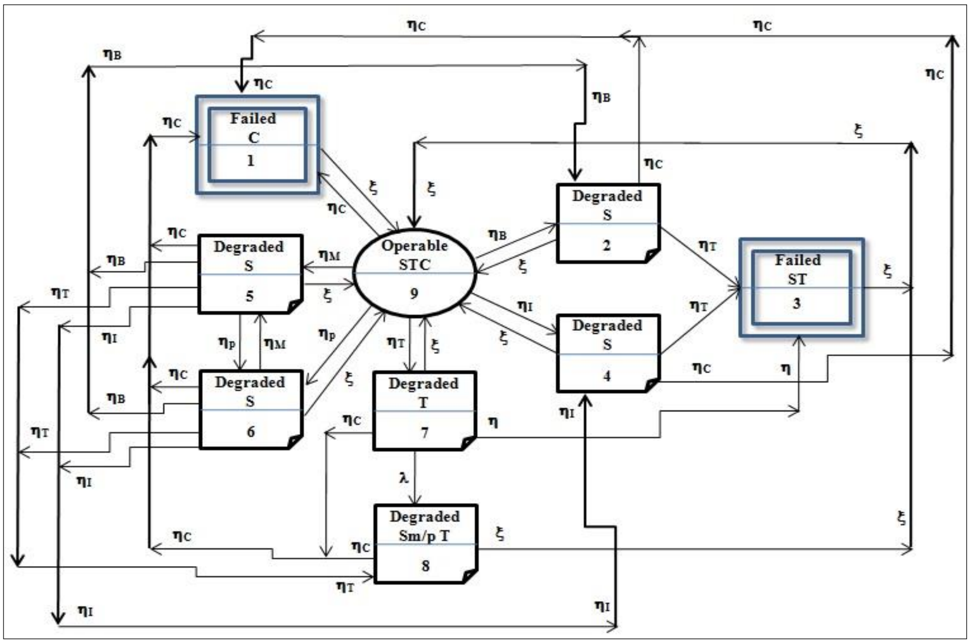

Figure 2. Transition Diagram of System States

Formulation of Mathematical Model:

By elementary probability theory, system parameters and continuity arguments, following probabilistic equations govern the behavior of the system:

$$P_1(t+\Delta t) = [1-(\xi)\Delta t]P_1(t) + \eta_c\Delta t P_4(t) + \eta_c\Delta t P_5(t) + \eta_c\Delta t P_9(t) + \eta_c\Delta t P_2(t) + \eta_c\Delta t P_7(t) + \eta_c\Delta t P_6(t) + \eta_c\Delta t P_8(t) \quad ...(1)$$

$$P_2(t+\Delta t) = [1-(\xi+\eta_T+\eta_c)\Delta t]P_2(t) + \eta_B\Delta t P_9(t) + \eta_B\Delta t P_6(t) + \eta_B\Delta t P_5(t) \quad ...(2)$$

$$P_3(t+\Delta t) = [1-(\xi)\Delta t]P_3(t) + \eta_T\Delta t P_2(t) + \eta \;\; \Delta t P_7(t) + \eta \;\; \Delta t P_8(t) + \eta_T\Delta t P_4(t) \quad ...(3)$$

$$P_4(t+\Delta t) = [1-(\xi+\eta_C+\eta_T)\Delta t]P_4(t) + \eta_i P_6(t)\Delta t + \eta_i P_5(t)\Delta t + \eta_i P_9(t)\Delta t \quad ...(4)$$

$$P_5(t+\Delta t) = [1-(\xi+\eta_B+\eta_c+\eta_i+\eta_T + \eta_P)\Delta t]P_5(t) + \eta_M\Delta t P_6(t) + \eta_M P_9(t)\Delta t \quad ...(5)$$

$$P_6(t+\Delta t) = [1-(\eta_C+\eta_i+\xi+\eta_M+\eta_T + \eta_B)\Delta t]P_6(t) + \eta_p P_5(t)\Delta t + \eta_P P_9(t)\Delta t \quad ...(6)$$

$$P_7(t+\Delta t) = [1-(\xi+\eta \quad +\eta_c+\lambda)\Delta t]P_7(t) + \eta_T P_5(t)\Delta t + \eta_T P_6(t)\Delta t + \eta_T P_9(t)\Delta t \quad ...(7)$$

$$P_8(t+\Delta t) = [1-(\xi+\eta+\eta_c)\Delta t]P_8(t) + \lambda P_7(t)\Delta t \quad ...(8)$$

$$P_9(t+\Delta t) = \left[1-\left(\eta_M+\eta_P+\eta_T+\eta_i+\eta_c + \eta_\beta\right)\Delta t\right]P_9(t) + \xi\Delta t P_5(t) + \xi\Delta t P_3(t) + \xi\Delta t P_8(t) + \xi\Delta t P_6(t) + \xi\Delta t P_7(t) + \xi\Delta t P_4(t) + \xi\Delta t P_1(t) + \xi P_2(t)\Delta t \quad ...(9)$$

Initial Conditions: Initially at $t = 0$, system is in completely working state (S_9), and the values of probabilities as $(0) = \begin{cases} 0 & when\ i \neq 9 \\ 1 & when\ i = 9 \end{cases}$

Solution of Mathematical Model with Numerical Interpretation:

Rewriting probabilistic equations 1 - 9, and taking $\lim_{\Delta t\to 0}$, the following resulting differential equations, corresponding reliability and cost function are obtained:

$$\frac{dP_1(t)}{dt} + \xi P_1(t) = \eta_c[P_2(t) + P_4(t) + P_5(t) + P_6(t) + P_7(t) + P_8(t) + P_9(t)] \quad ...(10)$$

$$\frac{dP_2(t)}{dt} + (\xi+\eta_c+\eta_T)P_2(t) = \eta_B[P_5(t) + P_6(t) + P_9(t)] \quad ...(11)$$

$$\frac{dP_3(t)}{dt} + \xi p_3(t) = \eta_T[P_2(t) + P_4(t)] + \eta[P_7(t) + P_8(t)] \quad ...(12)$$

$$\frac{dP_4(t)}{dt} + (\xi+\eta_T+\eta_C)P_4(t) = \eta_I[P_5(t) + P_6(t) + P_9(t)] \quad ...(13)$$

$$\frac{dP_5(t)}{dt} + (\xi+\eta_C+\eta_B+\eta_I+\eta_T + \eta_P)P_5(t) = \eta_M[P_6(t) + P_9(t)] \quad ...(14)$$

$$\frac{dP_6(t)}{dt} + (\xi+\eta_C+\eta_B+\eta_I+\eta_T + \eta_M)P_6(t) = \eta_P[P_5(t) + P_9(t)] \quad ...(15)$$

$$\frac{dP_7(t)}{dt} + (\xi+\eta_C+\lambda+\eta)P_7(t) = \eta_T[P_5(t) + P_6(t) + P_9(t)] \quad ...(16)$$

$$\frac{dP_8}{dt} + (\xi+\eta+\eta_C)P_8(t) = \lambda P_7(t) \quad ...(17)$$

$$\frac{dP_9(t)}{dt} + (\eta_C+\eta_B+\eta_I+\eta_P+\eta_M + \eta_T)P_9(t) = \xi[P_1(t) + P_2(t) + P_3(t) + P_4(t) + P_5(t) + P_6(t) + P_7(t) + P_8(t)] \quad ...(18)$$

Reliability, …(19)

$$R(t) = \sum P_i(t), \qquad i = 2,4,5,6,7,8,9$$

Cost Function ,

$$C_f = C_1 \star \int_0^t R(t)dt - C_2 \star t - C_3 \quad …(20)$$

where C_1 : Revenue cost, C_2: Repair cost per unit time and C_3 : Establishment Cost

Using MATLAB differential equation solver tool, the differential equations 10 - 18 are solved, by considering numerical values of failures

$$\eta_B = 0.015,\ \eta_I = 0.015,\ \eta_T = 0.02,\ \eta_M = 0.01,\ \eta_P = 0.01,\quad \eta = 0.01,\quad \lambda = 0.01$$

and evaluated the system reliability, specified in equation (19), for repairable ($\xi = 1$) and non-repairable ($\xi = 0$) system, under various values of consumption unit failure ($\eta_C = 0.02,\ 0.04, 0.06$). As well as, assess the cost function, given in equation (20), for distinct values of repair cost (C_2= 0.1, 0.2, 0.4, 0.6).

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Case I: Reliability for repairable system: Setting $\xi = 1$ in equation 19 and obtained the corresponding reliability function with respect to t for various values of $\eta_C = 0.02,\ 0.04,\ 0.06$.

Reliability for repairable system, R(t), for different values of consumption unit failure		
$\eta_C = 0.02$	$R_{0.02}(t) = \exp(-(26*t)/25)/26 + (3*\exp(-(103*t)/100))/206 - (7*\exp(-(107*t)/100))/214 + 280725/286546$	. . . (21)
$\eta_C = 0.04$	$R_{0.04}(t) = \exp(-(21*t)/20)/42 + (3*\exp(-(53*t)/50))/53 - (9*\exp(-(109*t)/100))/218 + 116570/121317]$	. . . (22)
$\eta_C = 0.06$	$R_{0.06}(t) = (2*\exp(-(27*t)/25))/27 + (7*\exp(-(107*t)/100))/214 - (11*\exp(-(111*t)/100))/222 + 100775/106893]$	. . . (23)

For different values of t, Fig. 3. exhibit, graphically, the values of equations 21 - 23.

Case II: Reliability for non-repairable system: Setting $\xi = 0$ in equation 19 and obtained the corresponding reliability function with respect to t for various values of $\eta_C = 0.02,\ 0.04,\ 0.06$.

Reliability for non - repairable system, R(t), for different values of consumption unit failure		
$\eta_C = 0.02$	$R_{0.02}(t) = \exp(-t/25) + \exp(-3*t)/100)/2 - \exp(-7*t)/100)/2$	. . . (24)
$\eta_C = 0.04$	$R_{0.04}(t) = \exp(-t/20)/2 + \exp(-(3*t)/50) - \exp(-(9*t)/100)/2$	. . .(25)
$\eta_C = 0.06$	$R_{0.06}(t) = \exp(-(2*t)/25) + \exp(-(7*t)/100)/2 -\exp(-11*t)/100)/2$	. . .(26)

For different values of t, Fig 4 reveals the values of equation (24) - (26) graphically.

Case III: Cost Function assessment: Setting C_1=1 and C_3=1 in equation 20 and evaluate the values of cost function with respect to t ,(using equation 21), for distinct values of C_2= 0.1, 0.2, 0.4, 0.6. The values of cost function are represented graphically in Fig. 5.

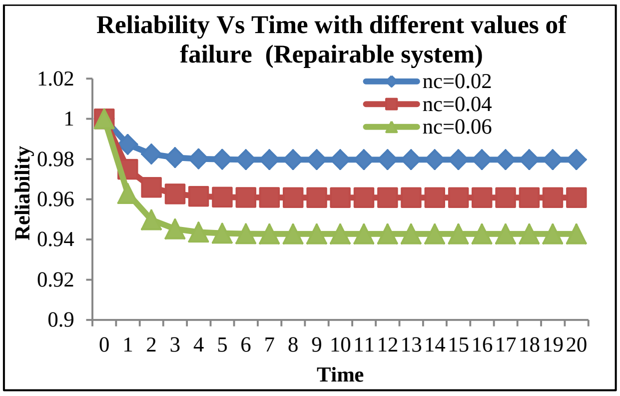

Figure 3. Reliability Vs Time (for repairable system)

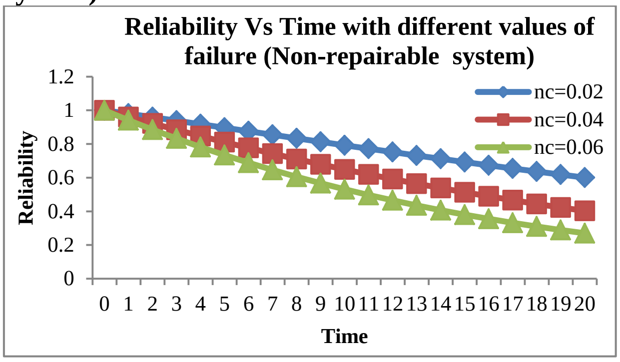

Figure 4. Reliability Vs Time (for non-repairable system)

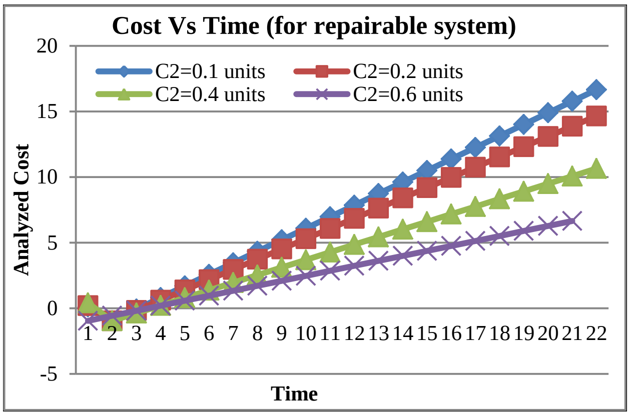

Figure 5. Cost Vs Time (for repairable system)

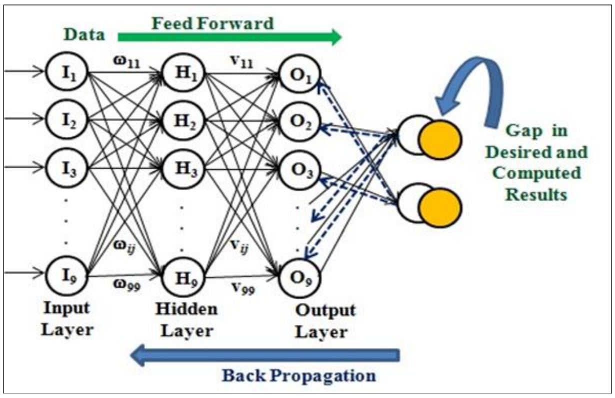

Figure 6. Neural Network Architecture

Solution of Model and Optimization of the Results with the Help of FFBPNN:

Considered, multilayered neural network (NN) structure is made up of neurons and consists of three layers, shown in Fig. 6. All layers are interconnected with synaptic links, called neural weights. These weights can be updating/ adjusting using learning algorithm associated with activation function to train the system, minimize the errors in results and optimize the results up to desired extend. Feed forward back propagation is one of the learning mechanisms of NN that approaches towards desired results quite promptly. Numerous states that are presented in Fig. 2, either in working or in failure mode, can be treated as neurons in input layer. These input neurons strongly connected with hidden layer neurons by neural weights and represent by weight matrix [W]. Hidden layer neurons connected with Output layer by neural weights and designated by weight matrix [V]. Failures and repairs are treated as neural weights. Feed forward back propagation (FFBP) learning mechanism is utilized to train the network. Working procedure of FFBPNN approach is as follows:

Step 1: Inputs in neural network are designated by I, and expressed mathematically by following equations:

$$I_i = P_i(t); \text{ where } i = 1, 2, \ldots, 9 \quad \ldots (27)$$

Step 2: Outputs of neurons are illustrated by O, and represent mathematically by the equations:

$$O_i = P_i(t + \Delta t); \text{ where } i = 1, 2, \ldots, 9 \quad \ldots (28)$$

Using equations 1 - 9, the output equations 29 - 37 are established, which are as follows:

$$O_1 = \omega_{11}I_1 + \omega_{21}I_2 + \omega_{41}I_4 + \omega_{51}I_5 + \omega_{61}I_6 + \omega_{71}I_7 + \omega_{81}I_8 + \omega_{91}I_9 \quad \ldots (29)$$

$$O_2 = \omega_{22}I_2 + \omega_{52}I_5 + \omega_{62}I_6 + \omega_{92}I_9 \quad \ldots (30)$$

$$O_3 = \omega_{33}I_3 + \omega_{23}I_2 + \omega_{43}I_4 + \omega_{73}I_7 + \omega_{83}I_8 \quad \ldots (31)$$

$$O_4 = \omega_{44}I_4 + \omega_{54}I_5 + \omega_{64}I_6 + \omega_{94}I_9 \quad \ldots (32)$$

$$O_5 = \omega_{55}I_5 + \omega_{65}I_6 + \omega_{95}I_9 \quad \ldots (33)$$

$$O_6 = \omega_{66}I_6 + \omega_{56}I_5 + \omega_{96}I_9 \quad \ldots (34)$$

$$O_7 = \omega_{77}I_7 + \omega_{57}I_5 + \omega_{67}I_6 + \omega_{97}I_9 \quad \ldots (35)$$

$$O_8 = \omega_{88}I_8 + \omega_{78}I_7 \quad \ldots (36)$$

$$O_9 = \omega_{99}I_9 + \omega_{19}I_1 + \omega_{29}I_2 + \omega_{39}I_3 + \omega_{49}I_4 + \omega_{59}I_5 + \omega_{69}I_6 + \omega_{79}I_7 + \omega_{89}I_8 \quad \ldots (37)$$

where ω_{ij} : neural weights from i^{th} state to j^{th} state

Step 3: Synaptic links in the form of neural weight in elapsed time Δt , between input and hidden layer are represented by weight matrix, [W] i.e.

$$W = \begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 7 \\ 8 \\ 9 \end{array} \begin{bmatrix} \in_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \xi\Delta t \\ \eta_C\Delta t & \in_2 & \eta_T\Delta t & 0 & 0 & 0 & 0 & 0 & \xi\Delta t \\ 0 & 0 & \in_3 & 0 & 0 & 0 & 0 & 0 & \xi\Delta t \\ \eta_C\Delta t & 0 & \eta_T\Delta t & \in_4 & 0 & 0 & 0 & 0 & \xi\Delta t \\ \eta_C\Delta t & \eta_B\Delta t & 0 & \eta_I\Delta t & \in_5 & \eta_P\Delta t & \eta_T\Delta t & 0 & \xi\Delta t \\ \eta_C\Delta t & \eta_B\Delta t & 0 & \eta_I\Delta t & \eta_M\Delta t & \in_6 & \eta_T\Delta t & 0 & \xi\Delta t \\ \eta_C\Delta t & 0 & \eta\Delta t & 0 & 0 & 0 & \in_7 & \lambda\Delta t & \xi\Delta t \\ \eta_C\Delta t & 0 & \eta\Delta t & 0 & 0 & 0 & 0 & \in_8 & \xi\Delta t \\ \eta_C\Delta t & \eta_B\Delta t & 0 & \eta_I\Delta t & \eta_M\Delta t & \eta_P\Delta t & \eta_T\Delta t & 0 & \in_9 \end{bmatrix}$$

where

$\in_1 = 1 - \xi\Delta t$

$\in_2 = 1 - (\xi + \eta_T + \eta_C)\Delta t$

$\in_3 = 1 - \xi\Delta t$

$\in_4 = 1 - (\xi + \eta_C + \eta_T)\Delta t$

$\in_5 = 1 - (\xi + \eta_B + \eta_C + \eta_i + \eta_T + \eta_P)\Delta t$

$\in_6 = 1 - (\eta_C + \eta_i + \xi + \eta_M + \eta_T + \eta_B)\Delta t$

$\in_7 = 1 - (\xi + \eta \quad + \eta_C + \lambda)\Delta t$

$\in_8 = 1 - (\xi + \eta \quad + \eta_C)\Delta t$

$\in_9 = 1 - (\eta_M + \eta_P + \eta_T + \eta_i + \eta_C + \eta_8)\Delta t$

Step 4: Synaptic links in the form of neural weight in elapsed time Δt , between hidden and output layer represent by weight matrix, [V] .

Step 5: Compute, Inputs of hidden layer (Ih) = Transpose of weight matrix [W] * Output of input layer

[Initially, output of input layer = input of input layer i.e. $I_i = P_i(t)$]

Step 6: Calculate, Output of hidden layer with the help of sigmoidal function

Step 7: Compute, Inputs of output layer (Io) = Transpose of weight matrix [V]* Output of hidden layer

Step 8: Calculate, Output of output layer with the help of sigmoidal function

Step 9: Compare the computed network output with desired output, termed as 'error'

Step10: If 'error' is greater than tolerance limit then adjust the weights [V] and [W] in back propagation manner using error correction gradient descent method, go to step 5 else end the training process

Step 11: Find the computed output up to the desired extent

Calculate the reliability and cost function using neural network, from output equations established in 29 - 37, and are written in the following manner:

Reliability ,

$$R(t) = \sum O_i \ , i = 2, 4, 5, 6, 7, 8, 9 \quad \ldots (38)$$

Cost function ,

$$C_f = C_1 * R(t) - C_2 * t - C_3 \qquad ...(39)$$

where C_1 : Revenue cost, C_2: Repair cost per unit time and C_3 : Establishment cost

Authors utilize MATLAB for coding feed forward backward propagation technique and assume following numerical values of failures and repairs

$\eta_B = 0.015, \quad \eta_I = 0.015, \quad \eta_T = 0.02, \quad \eta_M = 0.01, \quad \eta_P = 0.01,$
$\eta_C = 0.02, \quad \eta = 0.01,$
$\lambda = 0.01, \quad \xi = 1$

to establish the values of neural weights for repairable system and evaluate reliability and cost function. Table 1 shows the reliability values for some iterations, which approach to desired output up to 10^{-4} error tolerance and graphically depicts in Fig. 7. From equation 39, change in values of cost function, for C_1=1 unit, C_3=1 unit and distinct values of repair cost C_2= 0.1, 0.2, 0.4, 0.6 units, shows in Fig. 8.

Table 1. Reliability with iterations

Iterations	1	60	120	180	240	300	360	420	480	540	624
Reliability	0.6749	0.9702	0.9778	0.9815	0.9839	0.9859	0.9868	0.9878	0.9886	0.9892	0.99

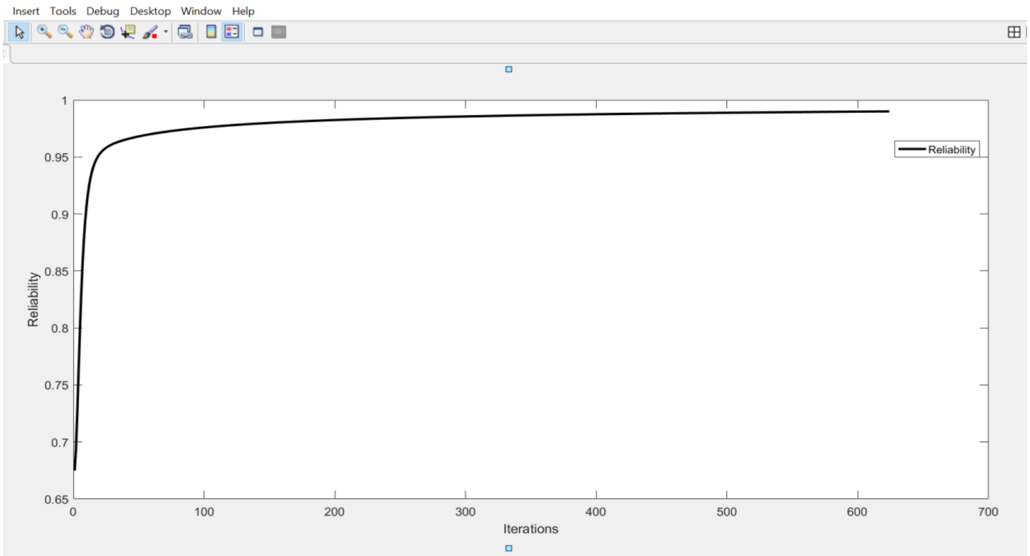

Figure 7. Optimized Reliability with iterations

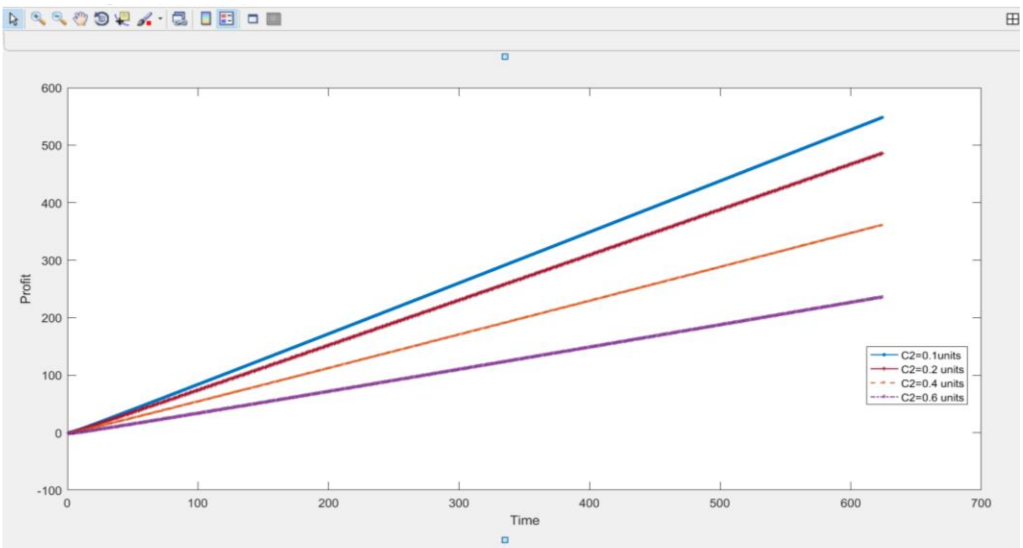

Figure 8. Cost Function with time

Discussion and Conclusion:

The results displayed through figures interpret the following facts:

- Figure 3 depicts the reliability of repairable system, initially 0.9873 that decreases with increase in failure rate of consumption unit and converges to a steady state value. On the other hand, reliability of non-repairable system start with 0.9798 decreases rapidly with time and with increases in failure rate of consumption unit as shown in Fig 4. Results are displayed in Fig 3 and 4 that show the non-working of consumption unit, η_C, which affects the system reliability.
- Figure 5 represents the values of cost function, for fixed value of establishment cost C_3, revenue cost C_1 and distinct values of repair cost C_2. Cost of the system initially is not satisfactorily but increases with time. It seems clearly that the cost of the function decreases with increases in repair cost with respect to time.
- Using FFBPNN algorithm, the reliability of the system is initially 0.6749 and optimized to 0.9900 by increasing the number of iterations, to obtain the desired reliability nearer to 1 and thus minimize the gap up to 0.0001 precision, as shown in Fig 7.
- The cost function is analyzed after optimizing the reliability, in Fig. 8, and reveals that there is remarkable increase in values of cost function with respect to time. But still cost of whole system decreases on increasing the repair cost. The values of cost function in Fig. 8 are significant in comparison to the values in Fig 5.

This paper studied $\mathcal{STC}$ model mathematically and optimize the results using FFBPNN learning mechanism. It highlights two main points, one about the consumption unit and cost, and second about improvement in the results. The system is affected by increasing the failure or deficiency in consumption unit. When on increasing the value of η_C (failure due to consumption units), reliability of system decreases with time. As well as for fixed values of establishment cost and revenue cost, and variable values of repair cost, the system cost increases. Thus, system analysts should take more care about consumption units or load and repair cost of the system. Reliability and cost can be improved by using FFBPNN technique. It reveals more valuable and effective results up to 99% with 10^{-4} tolerance using gradient descent algorithm for weights updating. This analysis stimulates NN approach is qualified to ensure the desired results. It is beneficial not only in the sense of reliability but also cost effectiveness. Consequently, it serves as a worthwhile utility for such applications in real time.

Authors' declaration:

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are mine ours. Besides, the Figures and images, which are not mine ours, have been given the permission for re-publication attached with the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee in KIET Group of Institutions.

Authors' contributions:

Ritu Gupta, Ekata, C.M. Batra contributed to the design and implementation of the research, to the analysis of the results and to the writing of the manuscript.

References:

1. Kaurav S, Yadav P. Hybrid Power System Using Wind and Solar Energy. Int J Inno Res Sci Engg Tech. 2016 Jan; 5(1): 54-58. Available from: DOI: 10.15680/IJIRSET.2015.0501007 .
2. Report of the Expert Group on 175 GW RE by 2022. Nat Ins Trans India Aayog. 2015. Available from: https://niti.gov.in/writereaddata/files/175-GW-Renewable-Energy.pdf.
3. Mudgal SM, Yadav AK, Mahajan V. Reliability Evaluation of Power System Network With Solar Energy. IEEE. 2020 Jul. Available from: DOI: 10.1109/ICPS48983.2019.9067364.
4. Muthusamy S, Meenakumari R. Optimal Planning of Solar PV/WTG/DG/Battery Connected Integrated Renewable Energy Systems for Residential Applications using Hybrid Optimization. Int J Indust Engg. 2018; 2(1):15-20.
5. Rausand M, Hoyland A. System Reliability theory. #2. New Jersey: John Wiley & Sons , Inc, Publication; 2004.
6. Balagurusamy E. Reliability engineering. India: Tata McGraw Hill Publishing Co. Ltd.; 1984.
7. Bazovsky Igor. Reliability Theory and Practice. NJ: PHI Englewood cliff; 1961.
8. Chauhan SK, Malik SC. Reliability Evaluation of Series-Parallel and Parallel-Series Systems for Arbitrary Values of the Parameters. Int J Stat Reliab Engg. 2016; 3(1): 10-19.
9. Paula CPD, Visnadi LBH, Castro FD. Multi-objective optimization in redundant system considering load sharing. Reliab Engg Sys Saf. 2019; 181: 17–27.
10. Gertsbakh IB, Shpungin Y. Models of Network Reliability: Analysis. Combinatorics, and Monte Carlo. London New York: CRC press Taylor & Francis Group; 2016.
11. Sanghavi M, Tadepalli S, Boyle T, Downey M, Nakayama M. Efficient Algorithms for Analyzing Cascading Failures in a Markovian Dependability Model. IEEE. Trans Reliab. 2017; 66(2): 258 – 280
12. Li XY, Huang HZ, Li YF. Reliability analysis of phased mission system with non-exponential and

partially repairable components. Reliab Engg Sys Saf. 2018 Jul; 175: 119-127.
13. Nandal J, Chauhan SK, Malik SC. Reliability and MTSF of series and parallel systems. Int J Stat Reliab Engg. 2015 May; 2(1): 74-80.
14. Levitin G, Xing L, Dai Y. Reliability versus expected mission cost and uncompleted work in heterogeneous warm standby multiphase systems. IEEE. Trans Sys Man Cybe Sys. 2017; 47(3): 462 – 473.
15. Gurney K. An introduction to neural networks. London: UCL Press; 1997.
16. Karunanithi N, Whitley D, Malaiya YK. Using neural networks in reliability. IEEE. 1992; 9(4): 53-59.
17. Lakshman I, Ramaswamy S. An Artificial Neural-Network Approach to Software Reliability Growth Modeling. Pro Comput Sci. 2015; 57: 695-702. Available from: https://doi.org/10.1016/j.ress.2018.08.012 .
18. Bisht S, Singh SB, Ekata. Reliability and profit function improvement of acyclic transmission network using artificial neural network. Mathe Engg Sci Aeros. 2020; 11(1): 127-141.
19. Quiles E, Roldán-Blay C, Escrivá-Escrivá G, Roldán-Porta C. Accurate Sizing of Residential Stand-Alone Photovoltaic Systems Considering System Reliability. MDPI. Sustaina. 2020 Feb 10; 12(3):1274- 1292. Available from: https://www.mdpi.com. DOI:10.3390/su12031274.
20. Arévalo JC, Rivera S, Santos F. Uncertainty cost functions for solar photovoltaic generation, wind energy generation and plug-in electric vehicles: Mathematical expected value and verification by Monte Carlo simulation. Int J Pow Ener Conv. 2019 March; 10(2):171-207.
21. Bhagat BA, Bhondve RR, Maske AV, Ravate SV, Karpe G. Hybrid Power Generation System using Wind Energy and Solar Energy. Int J Res Engg Sci Mngmt. 2019 February; 2(2): 805-808.
22. Yousif JH, Al-Balushi HA, Kazem HA, Chaichan MT. Analysis and forecasting of weather conditions in Oman for Renewable Energy Applications. Elsevier. Cas Stud Therm Engg. 2018 Nov. 15; 13: 1-12. Available from: https://doi.org/10.1016/j.csite.2018.11.006
23. Hussien ZK, Dhannoon BN. Anomaly Detection Approach Based on Deep Neural Network and Dropout. Bagh Sci J. 2020 Jun 23; 17(2): 701-709.
24. Shaikh MRS, Waghmare SB, Santosh B, Labade S, Tekale A. A Review Paper on Electricity Generation from Solar Energy. Int J Res App Sci Engg Tech. 2017; 5(IX): 1884-1889. Available from: www.ijraset.com. URL: https://doi.org/10.3390/su12031274 .

تقييم أداء نظام استهلاك المحولات الشمسية باستخدام طريقة الشبكة العصبية

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الخلاصة:

الطاقة الشمسية هي واحدة من الطاقة المتجددة التي لا حصر لها في توليد الطاقة لبيئة خضراء ونظيفة وصحية. تمتص الألواح الشمسية المكونة من طبقة السيليكون طاقة الشمس وتتحول إلى كهرباء بواسطة عاكس خارج الشبكة. نقل الكهرباء يتم إما من هذا العاكس أو من المحول، التي تستهلكها وحدة (وحدات) الاستهلاك المتاحة للأغراض السكنية أو الاقتصادية. الشبكة العصبية الاصطناعية هي أساس الذكاء الاصطناعي وتحل العديد من المشاكل المعقدة التي يصعب من خلال الأساليب الإحصائية أو من قبل البشر. في ضوء ذلك، فإن الغرض من هذا العمل هو تقييم أداء نظام الطاقة الشمسية - المحولات - الاستهلاك (STC). قد يكون النظام في حالة انهيار كامل بسبب فشل كل من النظام الفرعي لأتمتة الطاقة الشمسية والمحول في وقت واحد أو وحدة الاستهلاك ؛ وإلا فإنه يعمل بكفاءة كاملة أو أقل. يتم النظر في حالات الفشل والإصلاحات المستقلة إحصائيًا. يتم استخدام ظاهرة الاحتمالات الأولية المدمجة مع المعادلات التفاضلية لفحص موثوقية النظام ، للنظام القابل للإصلاح وغير القابل للإصلاح، ولتحليل دالة التكلفة الخاصة به. يمكن تحسين دقة واتساق النظام من خلال نهج الشبكة العصبية للانتشار الأمامي والخلفي (FFBPNN). يمكن لآلية تعلم النسب المتدرجة أن تقوم بتحديث الأوزان العصبية وبالتالي النتائج تصل إلى الدقة المطلوبة في كل تكرار، وبغض النظر عن مشكلة تلاشي التدرج في الشبكات العصبية الأخرى، مما يزيد من كفاءة النظام في الوقت الفعلي. تم تصميم كود MATLAB لخوارزمية FFBP لتحسين قيم الموثوقية ووظيفة التكلفة من خلال تقليل الخطأ إلى الحد الأدنى حتى 0.0001. يتم النظر في الرسوم التوضيحية العددية مع جداول البيانات والرسوم البيانية الخاصة بهم، لتوضيح النتائج وتحليلها في شكل الموثوقية ووظيفة التكلفة، والتي قد تكون مفيدة لمحللي النظام.

الكلمات المفتاحية: دالة التكلفة، خوارزمية الشبكة العصبية للانتشار الأمامي والخلفي، طريقة تحسين النسب المتدرجة، الموثوقية، الألواح الشمسية ذات طبقات السيليكون.