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

Ritu Gupta  E  Ekata * E  C.M. Batra E

Department of Applied Sciences, KIET Group of Institutions, Ghaziabad, India.
*Corresponding author: ekata@kiet.edu
E-mail address: ritu.gupta@kiet.edu, cm.batra@kiet.edu

Received 24/10/2020, Accepted 13/6/2021, Published Online First 20/1/2022

This work is licensed under a Creative Commons Attribution 4.0 International License.

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. 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. 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. 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.

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. Many authors discussed the failures and recovery modes of components and hence system performance. 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.

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. 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 upgrading 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.

The stand-alone photovoltaic residential generation system studied the uncertainties of solar radiation due to environmental conditions with component failures. Monte Carlo Simulation Method is used to evaluate the application of solar panels in a rigorous manner. Analysts recapitulated the availability, existing status, promotion policies and future possibilities of different forms of solar energy. 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.

This paper is designed to assess the reliability parameters and effective cost of Solar-Transformer-Consumption unit (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 (STC) system, consists of following subsystems:

1. **Subsystem 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 T - Transformer:** It connects with electricity power grid, commonly named hydel, and regulates electricity from consumption places to our residence or business.

3. **Subsystem 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 T works well. At this moment, if subsystem T fails, the system will fail completely. Similarly, if subsystem 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 S and T simultaneously. Failures of some of the solar panel(s) or monitoring unit reduce the efficiency of the system from either...
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 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:**
- \( \eta_B \) Constant failure when battery bank out of service
- \( \eta_I \) Constant failure when off-grid inverter out of service
- \( \eta_T \) Constant failure when transformer out of service
- \( \eta_M \) Constant failure when monitoring unit is not working
- \( \eta_P \) Constant failure when some solar panel(s) is not working
- \( \eta \) Constant failure when multiple units out of service simultaneously
- \( \eta_C \) Constant failure when consumption unit out of service
- \( \xi \) Constant repair when subsystem/unit repaired after facing failure

\[
P_i(t) \quad \text{system state probability at any time } t, \quad i = 1, 2, \ldots, 9
\]
\[
P_i(t + \Delta t) \quad \text{system state probability at time } t + \Delta t, \quad i = 1, 2, \ldots, 9
\]
Formulation of Mathematical Model:

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

\[ P_i(t + \Delta t) = \left[ 1 - (\xi) \Delta t \right] P_i(t) + \eta_i \Delta t P_0(t) \]
\[ + \eta_0 \Delta t P_i(t) + \eta_\tau \Delta t P_\tau(t) \]  
\[ + \eta_\tau \Delta t P_\tau(t) + \eta_\eta \Delta t P_\eta(t) \]

\[ P_\tau(t + \Delta t) = \left[ 1 - (\xi + \eta_\tau + \eta_\eta) \Delta t \right] P_\tau(t) \]
\[ + \eta_\eta \Delta t P_\eta(t) + \eta_\tau \Delta t P_\tau(t) \]

Initial Conditions: Initially at \( t = 0 \), system is in completely working state \( (S_0) \), and the values of probabilities as \( (0) = \begin{cases} 0 & \text{when } i \neq 9 \\ 1 & \text{when } i = 9 \end{cases} \)

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:

\[ \frac{dP_i(t)}{dt} + \xi P_i(t) = \eta_i \{ P_2(t) + P_3(t) \} \]  
\[ + P_0(t) + P_\tau(t) + P_\eta(t) \]  
\[ + P_\tau(t) + P_\eta(t) \]

\[ \frac{dP_\tau(t)}{dt} + (\xi + \eta_\tau + \eta_\eta) P_\tau(t) \]
\[ = \eta_\eta \{ P_5(t) + P_9(t) \} \]
\[ + \eta_\tau \{ P_5(t) + P_9(t) \} \]

\[ \frac{dP_\eta(t)}{dt} + (\xi + \eta_\tau + \eta_\eta) P_\eta(t) \]
\[ = \eta_\eta \{ P_5(t) + P_9(t) \} \]
\[ + \eta_\tau \{ P_5(t) + P_9(t) \} \]

Reliability,

\[ R(t) = \sum P_i(t), \quad i = 2, 4, 5, 6, 7, 8, 9 \]

Cost Function,

\[ C_f = C_1 * \int_0^t R(t) dt - C_2 * t - C_3 \]

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

\( \eta_B = 0.015, \eta_T = 0.015, \eta_\tau = 0.02, \eta_\eta = 0.01, \eta_\tau = 0.02, \lambda = 0.01 \)

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 \( (C_2 = 0.1, 0.2, 0.4, 0.6) \).
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 $\eta_C = 0.02, 0.04, 0.06$.

<table>
<thead>
<tr>
<th>$\eta_C$</th>
<th>$R(t)$ for different values of consumption unit failure</th>
</tr>
</thead>
<tbody>
<tr>
<td>$0.02$</td>
<td>$R_{0.02}(t) = \exp\left(-\frac{26t}{25}\right) + 280725/286546$</td>
</tr>
<tr>
<td>$0.04$</td>
<td>$R_{0.04}(t) = \exp\left(-\frac{21t}{20}\right)/42 + 116570/121317$</td>
</tr>
<tr>
<td>$0.06$</td>
<td>$R_{0.06}(t) = \exp\left(-\frac{27t}{25}\right)/27 + 100775/106893$</td>
</tr>
</tbody>
</table>

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 $\eta_C = 0.02, 0.04, 0.06$.

<table>
<thead>
<tr>
<th>$\eta_C$</th>
<th>$R(t)$ for different values of consumption unit failure</th>
</tr>
</thead>
<tbody>
<tr>
<td>$0.02$</td>
<td>$R_{0.02}(t) = \exp\left(-\frac{t}{25}\right) + \frac{1}{100}/2 + \frac{1}{100}/2$</td>
</tr>
<tr>
<td>$0.04$</td>
<td>$R_{0.04}(t) = \exp\left(-\frac{t}{20}\right)/2 + \exp\left(-\frac{3t}{50}\right)/2 - \exp\left(-\frac{9t}{100}\right)/2$</td>
</tr>
<tr>
<td>$0.06$</td>
<td>$R_{0.06}(t) = \exp\left(-\frac{2t}{25}\right) + \exp\left(-\frac{7t}{100}\right)/2 - \exp\left(-\frac{11t}{100}\right)/2$</td>
</tr>
</tbody>
</table>

For different values of $t$, Fig 4 reveals the values of equations (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.

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

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
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 \(I_t\) 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 \(O_t\) 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:

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

\[O_2 = \omega_{22}I_2 + \omega_{32}I_3 + \omega_{52}I_5 + \omega_{62}I_6 + \omega_{92}I_9 \quad \ldots (30)\]

\[O_3 = \omega_{33}I_3 + \omega_{23}I_2 + \omega_{33}I_4 + \omega_{73}I_7 + \omega_{83}I_8 + \omega_{93}I_9 \quad \ldots (31)\]

\[O_4 = \omega_{44}I_4 + \omega_{34}I_3 + \omega_{54}I_5 + \omega_{94}I_9 \quad \ldots (32)\]

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

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

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

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

\[O_9 = \omega_{99}I_9 + \omega_{89}I_8 + \omega_{79}I_7 + \omega_{59}I_5 + \omega_{69}I_6 + \omega_{99}I_9 \quad \ldots (37)\]

where \(\omega_{ij}\) : neural weights from \(i^{th}\) state to \(j^{th}\) state

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

\[
W = \begin{bmatrix}
\eta_{11} & \eta_{12} & \eta_{13} & \eta_{14} & \eta_{15} & \eta_{16} & \eta_{17} & \eta_{18} & \eta_{19} \\
\eta_{21} & \eta_{22} & \eta_{23} & \eta_{24} & \eta_{25} & \eta_{26} & \eta_{27} & \eta_{28} & \eta_{29} \\
\eta_{31} & \eta_{32} & \eta_{33} & \eta_{34} & \eta_{35} & \eta_{36} & \eta_{37} & \eta_{38} & \eta_{39} \\
\eta_{41} & \eta_{42} & \eta_{43} & \eta_{44} & \eta_{45} & \eta_{46} & \eta_{47} & \eta_{48} & \eta_{49} \\
\eta_{51} & \eta_{52} & \eta_{53} & \eta_{54} & \eta_{55} & \eta_{56} & \eta_{57} & \eta_{58} & \eta_{59} \\
\eta_{61} & \eta_{62} & \eta_{63} & \eta_{64} & \eta_{65} & \eta_{66} & \eta_{67} & \eta_{68} & \eta_{69} \\
\eta_{71} & \eta_{72} & \eta_{73} & \eta_{74} & \eta_{75} & \eta_{76} & \eta_{77} & \eta_{78} & \eta_{79} \\
\eta_{81} & \eta_{82} & \eta_{83} & \eta_{84} & \eta_{85} & \eta_{86} & \eta_{87} & \eta_{88} & \eta_{89} \\
\eta_{91} & \eta_{92} & \eta_{93} & \eta_{94} & \eta_{95} & \eta_{96} & \eta_{97} & \eta_{98} & \eta_{99}
\end{bmatrix}
\]

where

\[
\begin{align*}
epsilon_1 &= 1 - \xi \Delta t \\
\epsilon_2 &= 1 - (\xi + \eta_T + \eta_C)\Delta t \\
\epsilon_3 &= 1 - \xi \Delta t \\
\epsilon_4 &= 1 - (\xi + \eta_C + \eta_T)\Delta t \\
\epsilon_5 &= 1 - (\xi + \eta_B + \eta_C + \eta_i + \eta_T + \eta_P)\Delta t \\
\epsilon_6 &= 1 - (\eta_C + \eta_i + \xi + \eta_M + \eta_T + \eta_B)\Delta t \\
\epsilon_7 &= 1 - (\xi + \eta + \eta_C + \lambda)\Delta t \\
\epsilon_8 &= 1 - (\xi + \eta + \eta_C)\Delta t \\
\epsilon_9 &= 1 - (\eta_M + \eta_T + \eta_i + \eta_C + \eta_B)\Delta t
\end{align*}
\]

**Step 4:** Synaptic links in the form of neural weight in elapsed time \(\Delta t\), between input and hidden layer represent by weight matrix, \([V]\).

**Step 5:** Compute, Inputs of hidden layer (\(I_o\)) = 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 (\(I_o\)) = 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’

**Step 10:** 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:

\[
R(t) = \sum Q_i, i = 2, 4, 5, 6, 7, 8, 9 \quad \ldots (38)
\]
Cost function,
\[ C_f = C_1 * R(t) - C_2 * t - C_3 \] \( \ldots (39) \)
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:

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

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>
<thead>
<tr>
<th>Iterations</th>
<th>Reliability</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.6749</td>
</tr>
<tr>
<td>60</td>
<td>0.9702</td>
</tr>
<tr>
<td>120</td>
<td>0.9778</td>
</tr>
<tr>
<td>180</td>
<td>0.9815</td>
</tr>
<tr>
<td>240</td>
<td>0.9839</td>
</tr>
<tr>
<td>300</td>
<td>0.9859</td>
</tr>
<tr>
<td>360</td>
<td>0.9868</td>
</tr>
<tr>
<td>420</td>
<td>0.9878</td>
</tr>
<tr>
<td>480</td>
<td>0.9886</td>
</tr>
<tr>
<td>540</td>
<td>0.9892</td>
</tr>
<tr>
<td>624</td>
<td>0.99</td>
</tr>
</tbody>
</table>

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, $\eta_C$, 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 S$\eta$C 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 $\eta_C$ (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:
12. Li XY, Huang HZ, Li YF. Reliability analysis of phased mission system with non-exponential and
تقييم أداء نظام استهلاك المحولات الشمسية باستخدام طريقة الشبكة العصبية

روتو كوبتا

قسم العلوم التطبيقية، مجموعة مؤسسات KIET، غازي أباد، الهند

الخلاصة:
الطاقة الشمسية هي واحدة من الطاقة المتجددة التي لا حصر لها في توليد الطاقة لبيئة خضراء ونظيفة وصحية. تتضمن الألواح الشمسية المكونة من طبقة السيليكون طاقة الشمس، وتحولها إلى كهرباء بواسطة عاكس خارجي الشبكة. يتم الاختيار من هذا العاكس أو المحول، التي تستهلكها وحدة 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 تقني أداء نظام الاستهلاك - المحولات - المحولات (STC) ذات الطاقة الشمسية وتحليل دالة التكلفة الخاصة به. يمكن تحسين دقة النتائج من خلال استخدام الشبكة العصبية الاصطناعية، باستخدام تقنيات التعلم الآلي والذكاء الاصطناعي، مما يزيد من كفاءة النظام في الوقت الفعلي. يتم استخدام MATLAB وFFBPNN لتحسين قيم الموثوقية ووظيفة التكلفة من خلال تقليل الخطأ إلى الحد الأدنى حتى 0.0001. يتم الانتهاء من الرسوم التوضيحية مع جداول البيانات والرسوم البيانية الخاصة بهم، لتوضيح النتائج وتحليلها في شكل موثوقيات ووظيفة التكلفة، والتي قد تكون مفيدة لمحلي النظام. وتستند الكتب المصاحبة: "دار الكتالوج، خوارزمية الشبكة العصبية للانتشار الأمامي والخلفي، طريقة تحسين النسب المترابطة، الموثوقية، الأحواض الشمسية ذات نماذج بالبيئة".