Chapter

ANFIS TVA Power Plants Availability Modeling Development

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Abstract

In the present chapter, the evaluation of the Tennessee Valley Authority (TVA) Markov model transient behavior is derived and studied. It is focused on finding the models of the transient-state availability and unavailability of the four (TVA) models among using an adaptive neuro-fuzzy inference system (ANFIS). The developed ANFIS model for the TVA models is derived, and both availability and unavailability of the four TVA models are derived using the curve fitting technique, where each model of the transient availability of the three-state models of the TVA models is found. Each model is considered as a three-state model, and its equations obtained using the curve fitting technique are helping for the future availabilities and unavailabilities. The availability is a very important measure of performance for the availability of TVA power plants. The technique is used and applied on the four models in the present study to formulate and obtain the TVA models' results and are compared. In addition, the generation effects on the reliability investigation. The generation study evaluates the improvement in reliability over a time.

Keywords: transient availability, TVA, Markov model, ANFIS, curve fitting

1. Introduction

The Tennessee Valley Authority (TVA) is a business organization in the United States. TVA has been a key force for success in the Tennessee Valley since 1933 [1]. TVA supplies electricity to commercial customers and local energy supply companies. It serves approximately 10 million people in parts of seven southeastern states. TVA not only serves and invests its revenues in its electrical system but also provides flood control, navigation, and land management on the Tennessee River system and provides support to local energy companies.

Ren et al. [2] in their study went through the multi-microgrid system which is studied as a basic part of the intelligent network, and the radical system for several microgrids is the complete and standard system. The evaluation of the reliability of multi-microgrid systems is widely discussed to guarantee its reliability and steady-state operation. Balancing power between supply and demand is the key criterion for assessing the reliability of multiple microsystems, such as equipment shortages and inadequate distribution capacity in the network. In their research, few have developed a reliability model for partial failures and incomplete equipment repairs, and the transferability of distribution network (DN) is generally overlooked.
In their study, they summarize the multi-microgrid (MMG) radial system as a

performance sharing system and present a uniform modeling approach based on the Bayesian network for performance and reliability to fill research gaps. The operation of MMG radial systems is analyzed to create an abstract model to simplify the problem. The operational program is provided for the BN reliability assessment method. In addition, system modeling and BN parameter modeling are introduced. Finally, the MMG radial system composed of nine micronetworks (MNs) were examined and the variability of the system reliability indicator is analyzed in network-connected mode and in island mode.

Pham et al. [3] in their study highlight on the microgrid which mainly consists of distribution generators and energy storage systems, which are used to supply local loads. Distributed generators are mainly renewable energy sources. The aggregated system with numerous battery energy storage devices should be used to improve the reliability of the power supply from these renewable energy sources in the microgrid as a collective storage system battery power. The complete battery energy storage system is used to control the balance of source charging power so that microgrid can operate with high stability and reliability to supply electricity to a variety of customers. To demonstrate the importance of the complete battery energy storage system in microgrid, the reliability of its operation is examined in their study. Microgrid offers a systematic way to assess the reliability performance under various dynamic operational issues. An analytical method based on Markov models has been developed to assess the reliability of the entire energy storage system of the overall battery. In addition to the time-dependent failure rate, the voltage-dependent failure rate, and the power loss failure rate, important components, such as bilateral DC-to-DC converters, DC-to-AC converters, switching and protection devices, battery modules, and a battery charger/controller, are also designed and included in the reliability assessment. Depending on the dynamic operating problems of the microarrays with the full battery energy storage system and the photovoltaic (PV) generation systems, the overall battery energy storage system will be affected differently. The dynamic random operating conditions of the microgrid analyzed include the change in the load power, the intermittent and unstable operation of the PV sources, the modes of operation and distribution of the microarrays, and the cost/off-grid conditions. The complete battery energy storage system is used to control the balance of source charging power. The results of the simulation tests are presented and discussed to confirm that the operational reliability of the entire battery energy storage system in the microgrid strongly depends on its different dynamic operating strategies as well as activated voltage constraints.

Min et al. [4] in their paper highlight on the plan to switch to renewable energy, which recently has been a key element in the energy policy of the electricity system in South Korea. The renewable energy has raised questions about the reliability and flexibility of the electricity system. The researchers provide a research framework to assess the new policy in South Korea from different dimensions using three consecutive simulation models. The first-generation model in their study, which they derived from the best electricity generation mix, provides the overall cost of production and the environmental impact of the long-term capacity expansion plan. In addition, the researchers deal with other two simulation models to assess the reliability and flexibility of electrical systems, respectively. Also, they introduced the way to measure the results predictability of applying the framework in the new policy which shows that the policy does not guarantee a target level of reliability and increases costs and emissions. Achieving target system reliability requires additional reliability, and system flexibility is very sensitive to the type of capacity added.

Čepin, in his paper [5], published the modern electrical systems which introduce an increasing number of more dispersed and smaller energy sources, which are slowly replacing larger and more compact energy sources. The aim of the article is to examine the relocation of nuclear power plants to wind power plants to compare each scenario in terms of reliability of the electricity network. The author highlights on the load diagram and the variability of power plants. The load diagram power depends on environmental parameters over time. In addition, the article's updated method measures the power of the installation as a function of time instead of its nominal power. The first model, in the study, includes a dozen power plants including a nuclear power plant. This power plant will then be replaced by three wind turbines whose total power will be five times that of the nuclear power plant. Reliability is compared to pressure drop using actual weather data for a calendar year. The results show that a decrease in the reliability of the power system leads to a decrease in the reliability of the power system.

To determine the dynamic systems of a nuclear power plant, it is necessary to consider the effects of dynamic interactions, such as components, software, and operating processes. But at present, Lee et al. [6] in their study concentrate that there is no simple and easy-to-use tool to assess the availability of these dynamic systems. The method, for example the Markov chains, has a precise solution, but it is difficult to model the system. Using standard error trees, the reliability of a system with dynamic characteristics cannot be accurately estimated because error trees measure the reliability of a system configuration. The dynamic reliability graph with general gates (DRGGGs) allows intuitive modeling similar to actual system configuration, which can reduce the human error that occurs when modeling the target system. As the current dynamic reliability graph with general gates cannot assess the dynamic system in terms of reliability without repair, a new evaluation method enabling the availability of the dynamic repair system to be calculated is proposed through this study. The proposed method extends dynamic reliability graph with general gates by adding the repair condition to dynamic doors. A comparison of the method proposed by the Markov chains in terms of a simple validation model shows that the measured value converges toward the solution.

Sabouhi et al. [7] in their paper deal with the proper functioning of a power tool which depends on its subsystem and its components. Due to the current financial constraints in the energy sector, power plant operators face a wide range of challenges when dealing with the maintenance schedule and asset management practices. Knowing the roles and judgment of the components on the overall performance of the plant will help to plan for smooth, safe, and economical operation. To determine the technical and economic decisions for the maintenance of power plant equipment, this study focuses on modeling the reliability of combined cycle power plants (CCPPs). Reliability models are first developed for gas turbine power plants (GTPPs) and steam turbine power plants (STPPs), which provide the data needed to assess the overall reliability of the CCPP from a system perspective. Reliability indices with the reliability of the abovementioned types of supply devices are recommended to identify the critical components of a plant, that is, those which have the most significant impact on the reliability and availability objectives of the system. By identifying essential system components, it is possible to determine effective maintenance strategies for power tool components so that the available resources are well designed and technically allocated.

Uncertain sources of intermittent generation and load demand in addition to the transmission line access is not a threat to the security of electricity grids. In Sharifzadeh et al.'s [8] study, to address these uncertainties, an optimal stochastic energy flow is recommended when examining security constraints. A site generation method is also presented to assess the uncertainty of wind generations and load requests when evaluating their connections. In the proposed model, uncertainty is addressed through a combination of common decisions to be the best decision. The efficiency of the proposed model is demonstrated in the known 24 IEEE bus test system. The greater efficiency of the proposed model is shown numerically compared to four other definitive and stochastic methods for determining the reserve obtained and the "subsequent" conditions. In addition, the impact of the number of cases on the performance of the proposed model is assessed using a sensitivity analysis. Slower changes in the conditions created have also been shown to reflect correlations and can better capture the uncertain load behavior.

In recent years, there has been growing interest in developing maintenance activities for nuclear power plants in the form of risk-based models as studied by Mohammadhasani and Pirouzmand [9]. Maintenance design plays a key role in security likelihood assessment applications. The importance of these actions, especially when considering the effects of component degradation, is very clear for resolving controversial goals such as achieving the highest level of opportunity and reducing implementation costs of these actions, given the limitations of using standard safety assessment methods to test complex maintenance policies, as well as the difficulty of formulating the impact of component maintenance and degradation strategies using analysis of fault trees. Mohammadhasani and Pirouzmand [9] in their article present Markov's multi-time continuous approach to modeling three-component test and repair policies focusing on changing technical specifications such as test times. First, Markov models will be developed for three different test policies considering the effects of degradation. These models are then applied to analyze the availability of essential components of an emergency cooling system for the core of a VVER-1000/V446 nuclear power plant as a case study. In the first policy, the other components are not tested further. The test method is carried out in accordance with the test plan as originally recorded. In the second policy, additional testing should take place after the repair of the defective part and, in the third policy, the remaining redundant components should be subjected to extensive testing after the first detection.

Managing instant access to content servers (source servers) in a network in knowledge-centric networks has received little attention in Banerjee et al.'s [10] study. Banerjee et al. [10] considered a case in their study where content repositories in an information-centric network are temporarily unavailable, perhaps for reasons such as device malfunction, interruption of power outage, or denial of service attacks. Unlike the traditional host-centric Internet, users can still be served on information-centric networks, because content is stored on network nodes. The authors [10] begin their study by observing whether caches continue to operate using their native cache and expulsion policies after content repositories are unavailable, and over time the diversity of network content decreases. Therefore, the authors [10] recommend freezing network caches as soon as the custodians are not available. Next, the authors [10] provide a routing and search algorithm, content analysis under server availability, which uses breadcrumbs to efficiently find content stored on network nodes and to satisfy user requests when guards are not available. The authors [10] perform in-depth simulations of the real Internet topology in the Icarus simulator and show that content analysis on server accessibility can easily detect content stored on the network. The content of the server availability survey exceeds the shortest content demand on average by 56% and meets up to 98.5% of the total server demand.

2. Power plant model

The four TVA power plant models [11] are differing by nature of different numerical values for transition rates and are shown in **Table 1**. These transition rates are shown for the four TVA models represented by **Figure 1**, which are relevant to power plants operated by the TVA. Each TVA model is formed as illustrated in **Figure 2**, which is called Markov model. The general model for each of the TVA model can be represented by the following differential equations:

$$\frac{dP_{up}(t)}{dt} = -(a+b)P_{up}(t) + c\,P_{derated}(t) + d\,P_{down}(t) \tag{1}$$

$$\frac{dP_{derated}(t)}{dt} = a\,P_{up}(t) - (c+e)P_{derated}(t) + f\,P_{down}(t) \tag{2}$$

$$\frac{dP_{down}(t)}{dt} = b\,P_{up}(t) + e\,P_{derated}(t) - (d+f)P_{down}(t) \tag{3}$$

The three differential equations are solved using the MATLAB Simulink 7.10 package to find the transient probabilities of each model of the TVA, where the three states of each model are defined as follows:

Up-state: the system operates at full capacity.
Derated-state: the system operates at less than full capacity due to generators outages.
Down-state: the system has no power at all due to forced outage rate.

And the initial probabilities for each model are P1 (0) = 1, P2 (0) = 0, and P3 (0) = 0. The results are obtained for the four TVA models. The MATLAB Simulink 7.10 package is used to obtain the transient-state probabilities for the four TVA models and

Model	**Transition rates (per hour)**					
	a	**b**	**c**	**d**	**e**	**f**
1	0.0003	0.0010	0.0225	0.0350	0.0008	0.0004
2	0.0006	0.0050	0.0400	0.1000	0.0004	0.0004
3	0.0005	0.0002	0.0240	0.0430	0.0001	0.0001
4	0.0010	0.0006	0.0200	0.1000	0.0002	0.0020

Table 1.
The four TVA models' transition rate values [11].

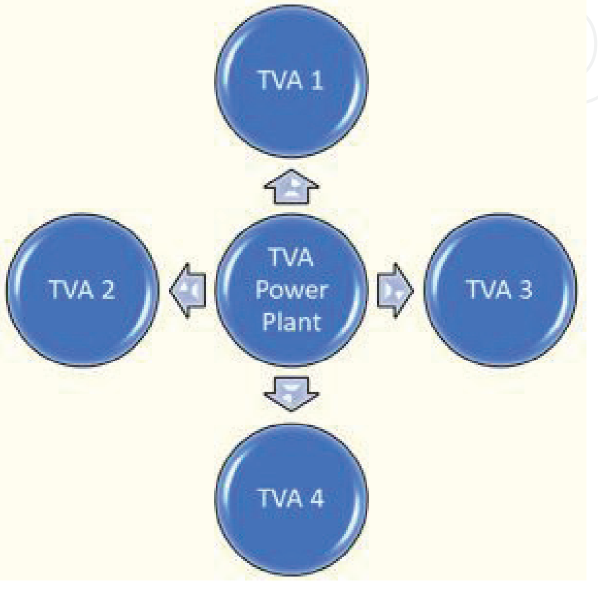

Figure 1.
TVA power plants' representation.

is reproduced by the fourth order Runge-Kutta method. Out of the obtained results, the availabilities and unavailabilities are obtained. The availability is the summation of the up-state and derated-state, where the unavailability is the down-state.

Table 2 summarizes the six transition rates of the four TVA models. **Figure 3a–d** illustrate the four TVA models with their transition rate values.

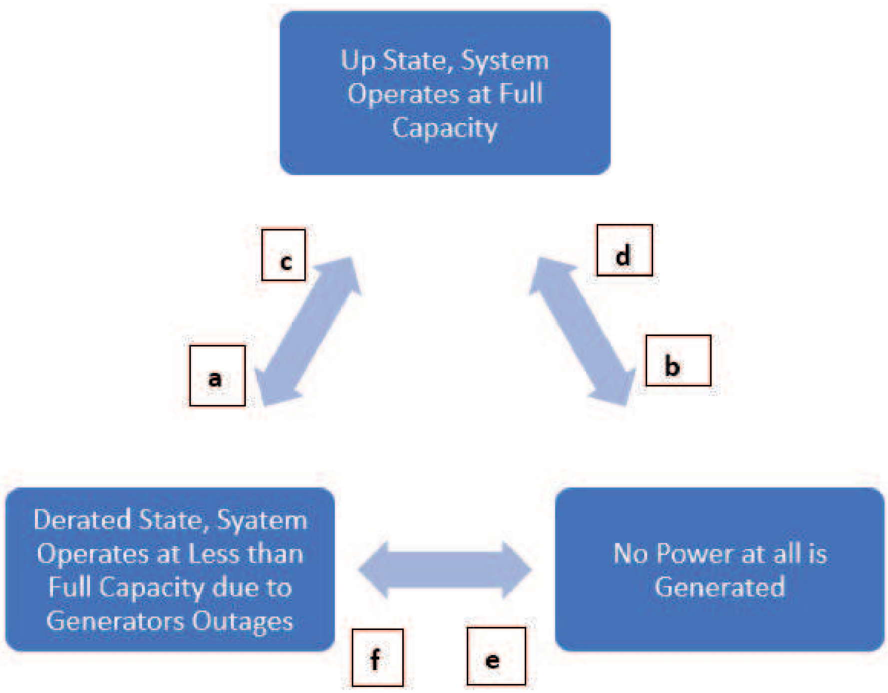

Figure 2.
TVA three-state Markov model.

Up-State → Derated-State → Transition Rate, a	Up-State → Down-State → Transition Rate, b
Derated-State → Up-State → Transition Rate, c	Down-State → Up- State → Transition Rate d
Derated-State → Down-State → Transition Rate, e	Down-State → Derated-State → Transition Rate, f

Table 2.
Transition rates of each TVA model.

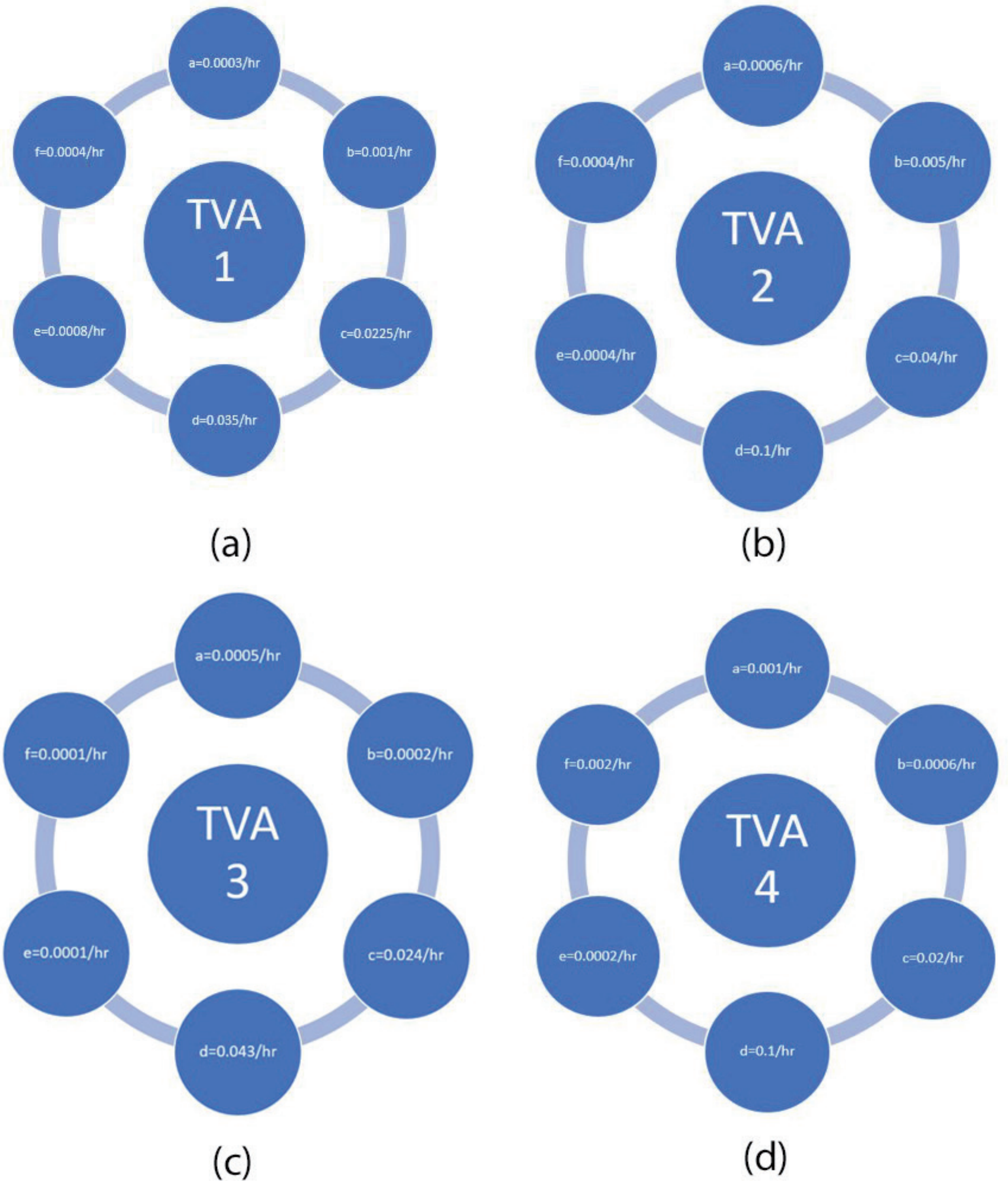

Figure 3.
Transition rate values for (a) TVA-1 model, (b) TVA-2 model, (c) TVA-3 model, and (d) TVA-4 model.

Al-Hamad and Qamber in their study [12] targeted a numerical evaluation of the nonlinear behavior of the Markov model and discussed it. Their study aims to obtain the transient probability between the states of four models recognized by the Tennessee Valley Authority (TVA). Three approaches are being studied to obtain the three transient probabilities after modeling. These techniques are Laplace transforms, curve fitting, and neuro-fuzzy. The MATLAB Simulink 7.10 package is used to obtain steady-state probabilities for the four VAT models while reproducing these solutions with Laplace transforms. For each model, a three-state model is considered, where its equations can be obtained using curve fitting and neuro-fuzzy methods. All the methods are used and applied in Al-Hamad and Qamber's study [12] and are used to design and obtain the TVA models. Al-Hamad and Qamber's study [12] proposes three technical approaches. These techniques increased the performance of the models in terms of execution time. These techniques are Laplace transformations, curve fitting, and neuro-fuzzy. The main objective of their study [12] is to temporarily reshape the transient-state probabilities for the four TVA models and find the best TVA models, even if any researcher has worked on modeling using curve fitting and other methods. TVA data are very useful for modeling a three-state model system. In their work the neuro-fuzzy was studied and used. It is found that it is the best and most useful to model and calculate the transient probabilities. In addition, the performance of the TVA models is clear and satisfying. As the way of calculating the transient probabilities throughout the operation period, each TVA model is likely to be trained at some point to develop fuzzy IF-THEN rules that help to determine the input and output variables for the functions of the TVA model. In Al-Hamad and Qamber's study [12], the combination of fuzzy logic and the neural network (becoming neuro-fuzzy) is a powerful means of designing intelligent systems and obtaining precise results. In their study [12], curved fitting modulation methods and neuro-fuzzy methods were adopted and applied to the four TVA models to calculate the probability of nonlinear state of the models. The performance of the two approaches was also evaluated to find the right and the accurate approach for the four TVA models. The results obtained from Al-Hamad and Qamber's study [9] were found to be much closer to the results of Laplace transforms, in particular, the results obtained using neuro-fuzzy. The study [12] shows a successful development of a reliable relationship between the probabilities of movement and time. Results obtained with both curve fitting and neuro-fuzzy were compared and studied. Comparing exposures to neuro-fuzzy offers better accuracy—as already mentioned—in predicting the probability of a moving state carried out in their study [12].

3. Applications and results

The neuro-fuzzy has a combination of advantages of the neural networks and fuzzy-logic, where the aim of the neuro-fuzzy is to combine collectively the benefits of both approaches. The neural networks have two main benefits. These two can learn nonlinear mapping of numerical data and the performing of parallel computation. It is very hard to understand the meaning of weights and the incorporation of prior knowledge into the system, which is usually impossible. Fuzzy logic uses human understanding of linguistic terms to form the knowledge of the system. This makes a close interaction between the system and human operator possible. In addition, neuro-fuzzy systems allow the incorporation of both numerical and linguistic data into the system, where it is also capable of extracting fuzzy knowledge from numerical data.

The ANFIS system applies the artificial neural network to find a suitable fuzzy inference system (FIS) structure and parameters. The fuzzy system with its structure identifies the considered fuzzy rules to obtain the targeted results. In addition, the considered architecture of the ANFIS structure has five layers as shown in **Figure 4**, which is the developed model in the study.

The developed general model for the neuro-fuzzy system is shown in **Figure 4**. **Figure 4** shows the developed five-layer connection for six inputs and two outputs. These five layers represent the neuro-fuzzy model, which is used to represent the TVA models and helps to obtain the availabilities and unavailabilities of each TVA model.

The proposed model using the neuro-fuzzy has six inputs as mentioned earlier and two outputs model as illustrated in **Figure 4**. In addition to the fourth order Runge-Kutta method, ANFIS technique applied in the present chapter to model the three-state probabilities of the four TVA models (fourth layer of **Figure 4**) which deals to the fifth layer helps to find the availability and unavailability of the model. The availability is reaching the steady-state availability of each TVA

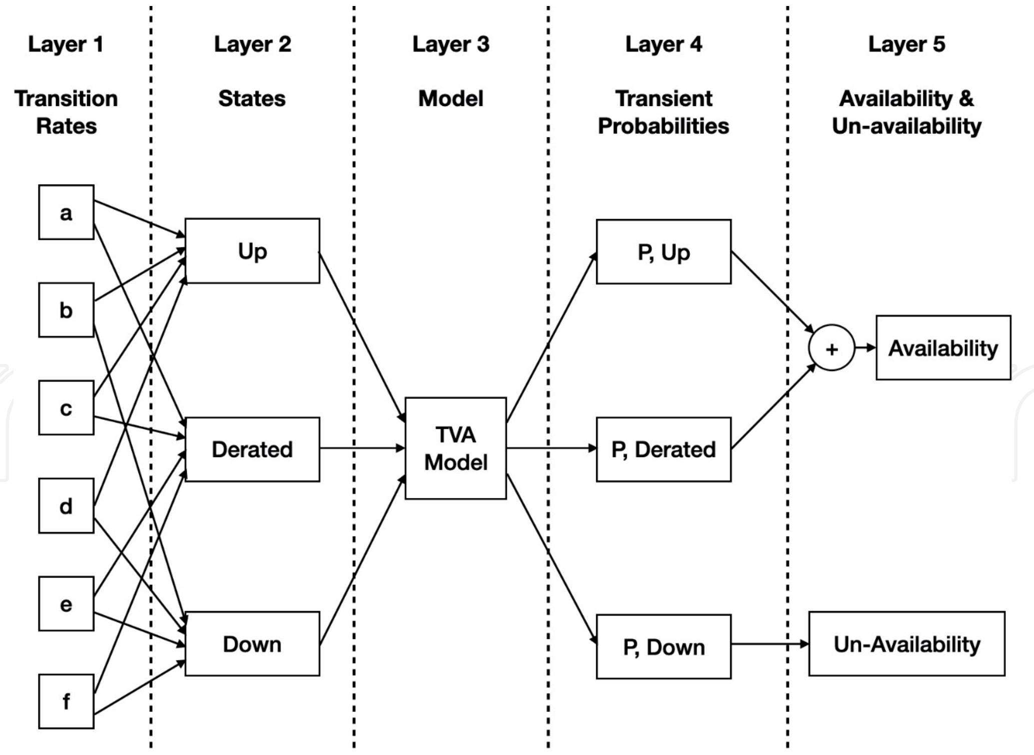

Figure 4.
ANFIS TVA developed model.

model, where the steady-state availability is defined as the steady-state probability of the system which is IN service. The steady-state probability that the TVA model is OUT of service is calculated as out of service due to failures. Any system can be interpreted as the long-run fraction of time spent in the failure state. The ANFIS and the curve fitting techniques are compared based on the availability and unavailability results. Through the obtained results, it is found that the results from both techniques are very close to each other. ANFIS and the curve fitting models are identical.

With reference to the TVA models, the fuzzy inference system (FIS) is applied. Six inputs are shown in layer (1), which are the transition rates between the three states model (**Figure 2**). The outputs of the model (layer (5)) results are the availability and unavailability of the TVA model. The second layer shows the three-states model. This process of converting an output fuzzy set for a solution variable into a single model is represented by the layer (3) which is TVA model. The results of the TVA model are shown in layer (4), which are the three probabilities P_{Up}, $P_{Derated}$, and P_{Down}.

The results obtained using the curve fitting for the four TVA models are shown in **Figures 5–8** as availability and unavailability. The curve fittings models' equations are obtained for the four TVAs' availability and unavailability as a function of time.

The availabilities as a function of time for the four TVA models are shown in **Figures 5a**–**8a**, respectively. The availability of each TVA model decreased gradually with time and then finally reached steady state (stable). The unavailability of each TVA model is illustrated in **Figures 5b**–**8b**, respectively. The unavailability of each TVA model increased gradually till it reached the steady state (stability).

When the generation reached the stability, the availabilities are 98.72%, 98.56%, 97.99%, and 95.26%, respectively, for the corresponding TVA models. Under the same conditions, the unavailabilities are 1.28%, 1.44%, 2.01%, and 4.74%, respectively, for the TVA models.

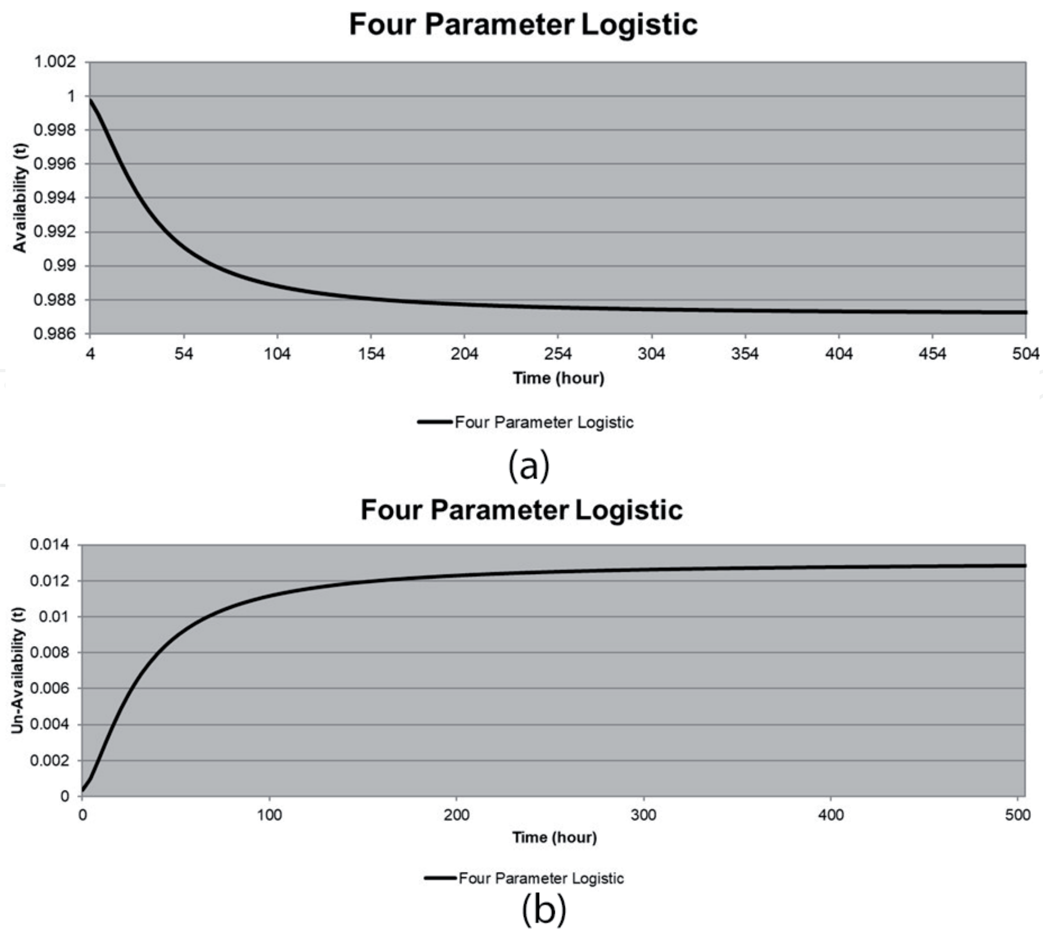

Figure 5.
(a) Availability model for TVA1 and (b) unavailability model for TVA1.

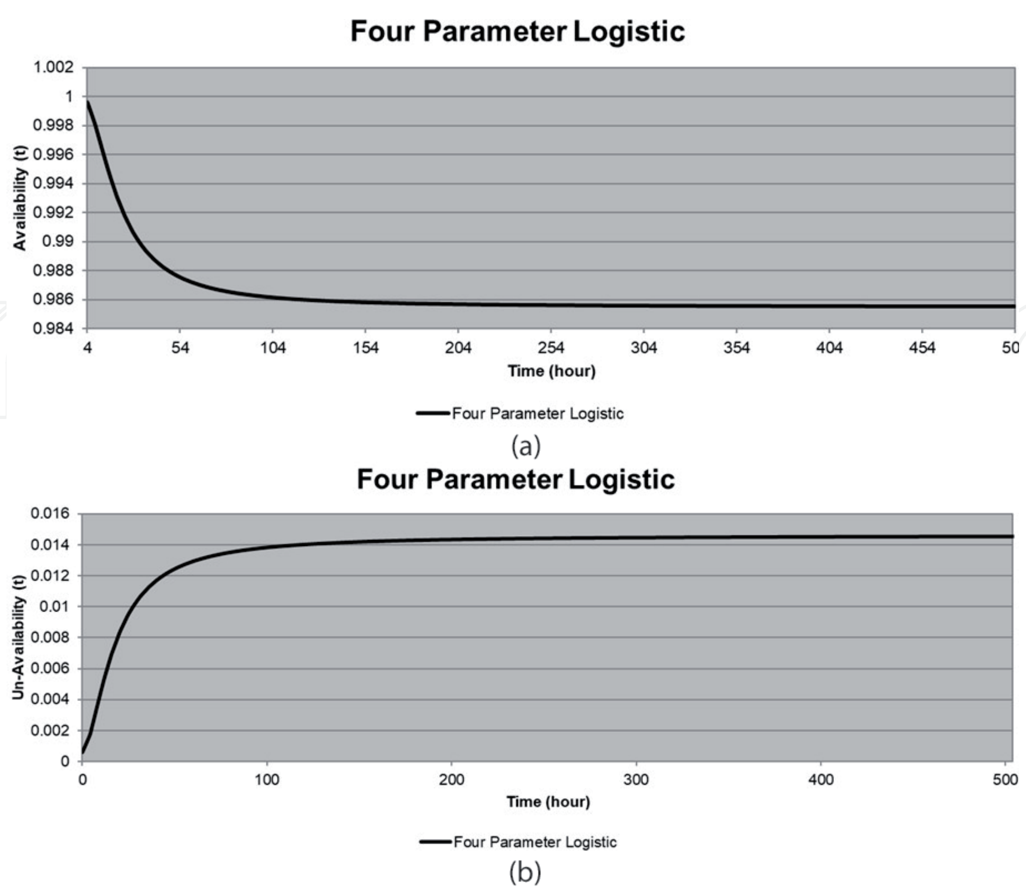

Figure 6.
(a) Availability model for TVA2 and (b) unavailability model for TVA2.

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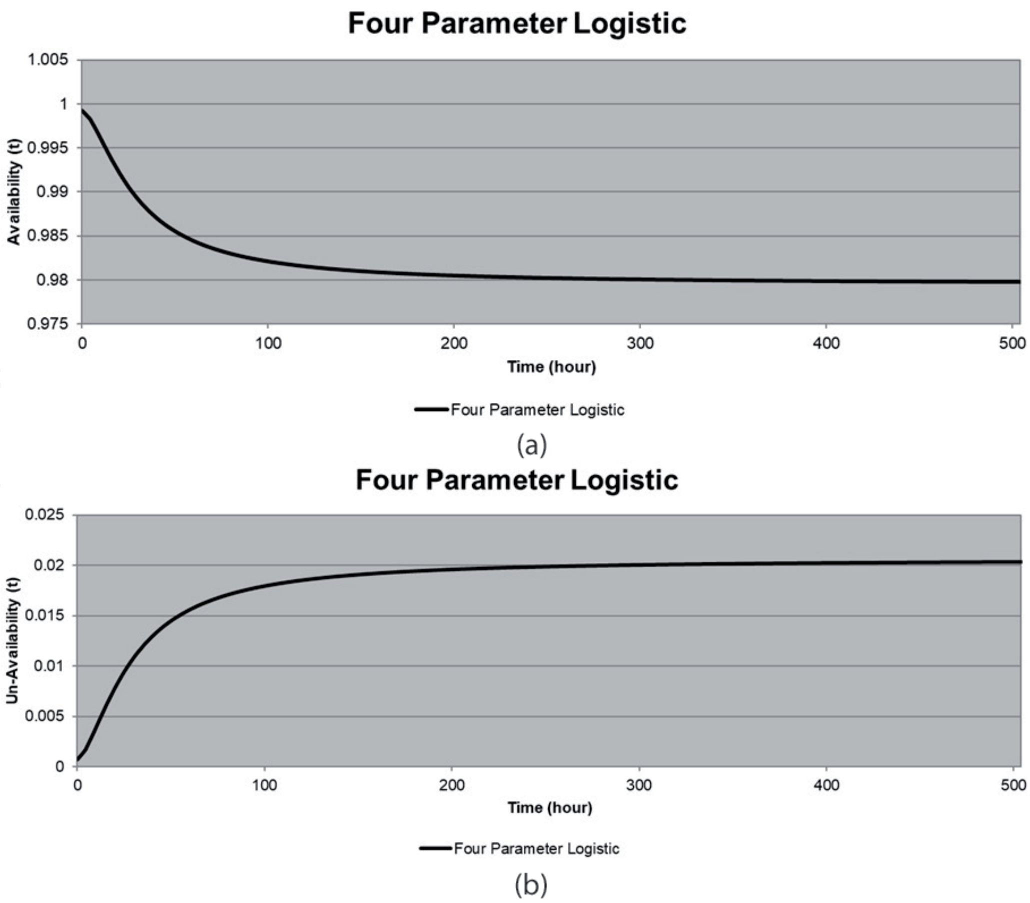

Figure 7.
(a) Availability model for TVA3 and (b) unavailability model for TVA3.

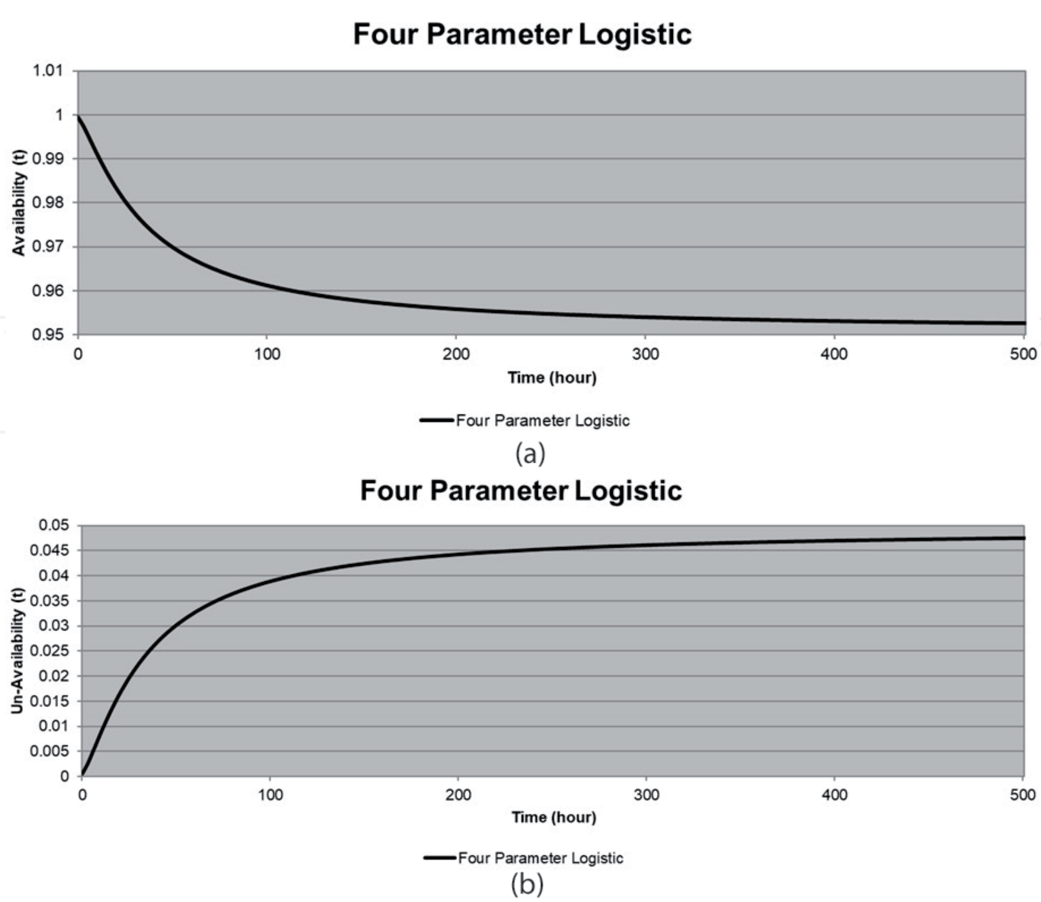

Figure 8.
(a) Availability model for TVA4 and (b) unavailability model for TVA4.

The curve fitting technique MyCurveFit (online curve fitting) is applied to find the model as shown in **Figures 5–8** as mentioned earlier. The results for the four TVA models are summarized in **Table 3**, showing the availabilities of each model, where **Table 4** shows the unavailabilities of the same models. The obtained availability equation using the curve fitting technique MyCurveFit is shown in Eq. (4) for the four TVA models.

$$Availability\left(time\right) = d + \frac{\left(a-d\right)}{1+\left[\frac{Time}{c}\right]^{b}} \tag{4}$$

The obtained unavailability equation using the curve fitting technique MyCurveFit is shown in Eq. (5) for the four TVA models.

$$Un - Availability\left(Time\right) = d + \frac{\left(a-d\right)}{1+\left[\frac{Time}{c}\right]^{b}} \tag{5}$$

Strong access to a complex system, such as a gas turbine, is linked to a part's reliability and maintenance policy. This policy affects not only the repair time of parts but also the reliability of parts, which affects the contamination and accessibility of the system. In any study, different methods are used for assessing the reliability and availability of gas turbines installed in a power plant. The investigated methods are based on concepts of system reliability, such as the development of the functional tree structure. The application of the failure mode and the analysis of the power

Availability model of TVA		Coefficients
TVA1	a	1.00014234742424
	b	1.646673111807
	c	32.8722769925419
	d	0.98712380612843
TVA2	a	1.00022688188532
	b	1.89339095988375
	c	20.6089357501677
	d	0.985496773685337
TVA3	a	0.999265231533308
	b	1.53764424728804
	c	29.218900622036
	d	0.97949890714863
TVA4	a	0.999505792270978
	b	1.26046003465127
	c	35.1534160245152
	d	0.950859080757418

Table 3.
Availabilities of the four TVA models.

Unavailability model of TVA		Coefficients
TVA1	a	0.000369658874527318
	b	1.47698177420345
	c	30.6343647596028
	d	0.0130413214169725
TVA2	a	0.000583437614778953
	b	1.64413595811526
	c	17.7140736131654
	d	0.0146075810962714
TVA3	a	0.000728795178208125
	b	1.52929468363619
	c	29.3840092626888
	d	0.0205824453759151
TVA4	a	0.000499149643278974
	b	1.26083143262919
	c	35.1382710744811
	d	0.0491382311673703

Table 4.
Unavailabilities of the four TVA models.

supply helps identify the critical components in improving the reliability of the system. The system and assessment of maintenance based on a historical fault database. This study focuses on the transition rates' changes (failure and repair rates) between the state which the model is passing through as observed and presented in this study. Implement trust-based maintenance concepts to implement the complex system maintenance policies of the generation system aimed at minimizing unexpected failure in critical components. The accessibility analysis shows different results for each TVA model, showing differences in the installation and operation of the system.

4. Conclusion

Various failure and repair transition rates have been taken in consideration in the present study. In the present study, the transition rates show the performance of the TVA models based on their variation and nature of each model. Different cases as obtained graphs show the availability and unavailability of the TVA models, where their models are produced by the curve fitting. The availability and unavailability values are obtained through a period of times. The unavailability increases until it is finally becoming stable.

The reliability of the availability and unavailability generation study seems important to obtain the means for the designer to apprehend the reliability for each design of TVA model. This means that the experience feedback is necessary. In the present study, the main part is to obtain the general TVA model transient availabilities and unavailabilities which has been modeled. This leads to the final target of the application study.

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Conflict of interest

The authors declare no conflict of interest.

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