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ESTIMATION TYPES OF FAILURE FOR THERMO-ELECTRIC UNIT BY USING ARTIFICIAL NEURAL NETWORK (ANN)

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Abstract

Frequent failure in production systems is one of the most important problems facing maintenance planners. In this paper, the methodology for estimating failure in an electrical energy production system has been proposed. Consisting of a number of related sub-systems, respectively, failure of any one causes the rest to stop producing. Operating data were collected and the type of failure identified, which was classified into three types (mechanical failure, electrical failure, and control failure). The software (Matlab) was used in generating and training an artificial neural network (ANN) to estimate the type of failure, through the data collected for each sub-system of the unit under study, use 90% of the data for training, 5% for testing, and 5% for valuation. The target matrix was built and trained, with a mean square error (MSE) its(6.54 E-16), and regression (91%), and adopted to estimate the type of future failure for subsequent years(2019),conformance results were for the subsequent year between (82%-87%) for all the subsystems.

Using the artificial neural network, failure types were estimated for another subsequent year (2020), the failure ratios were for subsystems for every ten days during the year of estimation, were (33%) for the generator, (22%) for the boiler, (31%) for the turbine, and (13%) for the condenser. High percentages, which can be reduced by taking advantage of the proposed methodology that gave an understanding of the type of failure, the time it occurred, and the location of the failure, by building an overlapping preventive maintenance plan whose application is approved in reducing the failure times of the unit under study. The proposed methodology can also be applied to all other systems of different production.

Keywords : Matlab software, Artificial Intelligent (AI) , Generator.

I. Introduction

Most modern industries avoid sudden maintenance that occurs in equipment, in order to reduce workloads and costs, scheduled maintenance that follows modern methods of predicting failure before it occurs, mitigate this, using (ANN) as an important tool applied in scheduling, preventive maintenance and making the appropriate decision to conduct them [VI].The theory of estimation is a branch of modern statistical science that relies mainly on analyzing the input parameters and making use of its results in obtaining the output parameters [X]. ANN has an important roles in deferent applications, It has an effective role in forecasting processes in various fields [IX]. The (ANN) consists of a large number of simple processors an element called neurons, units, cells, or nodes. Each neuron is connected to the other neurons by means of direct communication links, each with an associated weight. The weights represent the information being used by the net to solve the problem [VII]. Estimated is one of the statistical methods that rely on previous information and data documented in a manner that helps researchers in the field of development and improvement to build the scientific decision studied in the scheduling of maintenance [II], Devika Chhachhiya, et al (2014) [I], research paper in which the (MATLAB Toolbox) software, was used in the generation and training of a (ANN), on the classification of data for glass materials, he used an developed algorithm to identify errors that gave accurate results in determining the types of additives for the production process. Farhad Hooshyaripor et al (2015) [V], This paper estimates the amount of flow from dams, by training ANN to record failure data and use the effect of parameters (water volume and height). The network performance is acceptable, since it cannot guess a flow of less than 100 m3 / s. Erdi Tosun, Ahmet C¸ alık (2016) [IV], The research expected of pregnancy failure in the joint by training the neural network on data related to the length and width parameters as input to the network and the load is the output, the network gave effective and acceptable results in estimation. Emilia Sipos, Laura-Nicoleta Ivanciu (2017) [III], This paper presents how to predict the failure that occurs in the manufacture of chips, based on daily data and using the artificial neural network and diagrams such as Pareto, the future values of failure have been estimated. Mahdi Saghafi, Mohammad B. Ghofrani (2018) [VIII] This paper provides an estimate of the size of the fracture in the coolant tubes in the nuclear power plant using the (NARX algorithm in ANN) using the time parameter as a input to the network, the network demonstrated its ability to estimate the fraction satisfactoril. Scalabrini Sampaio, et al (2019) [VI], the researcher used the neural networks to estimate the failure in the motor by amount data used in training the network. The network demonstrated the ability to schedule a preventive maintenance of industrial equipment and machinery.

From the literature, very few researches have been done on the type of failure using ANN. Therefore, in this study an ANN model was developed to predict the type of future failure. The developed ANN model is used to analyze the effect of process parameters at the time of failure and operating time of the system during three years (2015-2017), and the year 2018 was used as a test year to check the modeling work, and validate Experimental results before developing a model.

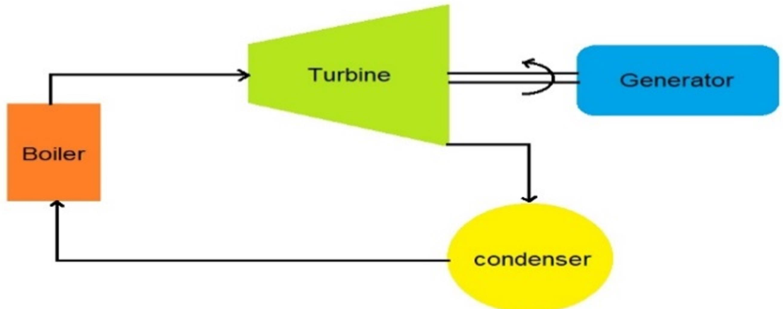

Fig. 1: The system under study

II. Case Study

Fig. 1 shows the generation system under study, and its sub-systems, table 1 shows the operation and stopping time data from four years (2015-2018), the type and location of the failure are shown in the table too, failures are classified according to three types (mechanical, electrical, and control), the failure times and the time taken for maintenance are clearer in the hours, as well as the date, year and hour for it to occur.

Table 1: The operation and stopping time for a unit under study.

I	`operation time	Stopping time	Period time		Subsystem of unit				Type of failure
			From[hr]	To[hr.]	Condenser	Generator	Turbine	Boiler	
	1/1/2015 12:00 AM	19/1/2015 4:00 PM	0	448	low vacuum				Mechanical
	19/1/2015 5:00 PM	30/5/2015 4:30 PM	449	3592.5			Check Vibration		Mechanical
	31/5/2015 4:30 AM	31/5/2015 10:30 AM	3604.5	3610.5			Check Vibration		Mechanical
	31/5/2015 1:30 PM	14/6/2015 11:00 AM	3613.5	3947			Electrical hydraulic suddenly open		Control

	14/6/2015 12:45 PM	2/7/2015 10:15 PM	3948.75	4390.25				shutdown	Mechanical
	3/7/2015 2:45 AM	16/7/2015 4:30 PM	4394.75	4720.5		signal under voltage			Electrical
	16/7/2015 6:00 PM	19/7/2015 1:45 PM	4722	4789.75		high temp in room exciter			Electrical
	19/7/2015 2:30 PM	19/7/2015 9:30 PM	4790.5	4797.5			Control room		Mechanical
	19/7/2015 10:30 PM	15/8/2015 11:30 PM	4798.5	5447.5				Replay valve 5 NM 28 safety	Mechanical
	16/8/2015 2:30 AM	27/8/2015 11:45 AM	5450.5	5723.75		signal under voltage			Electrical
	27/8/2015 1:15 PM	31/8/2015 2:30 PM	5725.25	5822.5				Trip by signal drum level high	Mechanical
	31/8/2015 6:00 PM	6/9/2015 3:30 PM	5826	5967.5		over current			Electrical
	6/9/2015 6:00 PM	8/10/2015 11:45 PM	5970	6743.75	push button fire				Mechanical
	9/10/2015 10:15 AM	28/10/2015 6:30 PM	6754.25	7218.5			Trip by signal I.P.S.LOGIC		Control
	29/10/2015 7:00 PM	2/11/2015 10:00 AM	7243	7330				Trip by signal (lose of both	Mechanical

								F.D.F G.R.F	
.	**2/11/20 15 9:00 PM**	**16/11/2 015 7:15 AM**	**7341**	**7663.2 5**	**Low vacuum**				**Mechan ical**
.	**16/11/2 015 5:15 P**	**21/11/2 015 9:30 PM**	**7673.25**	**7797.5**			**High Prussure**		**Mechan ical**
.	**23/11/2 015 5:30 AM**	**6/12/20 15 11:15 AM**	**7829.5**	**8147.2 5**				**Vacum low low**	**Mechan ical**
.	**6/12/20 15 12:15 PM**	**10/12/2 015 4:30 PM**	**8148.25**	**8248.5**				**Steam Leakag e in control valve**	**Mechan ical**
.	**13/12/2 015 2:30 AM**	**13/12/2 015 2:00 PM**	**8306.5**	**8318**			**High vibration bearing**		**Mechan ical**
.	**17/12/2 015 12:30 PM**	**27/12/2 015 12:00 PM**	**8412.5**	**8652**		**Loses power**			**Electric al**
.	**27/12/2 015 2:15 PM**	**26/1/20 16 12:15 AM**	**8654.25**	**9360.2 5**			**Low vacuum**		**Mechan ical**
.	**26/1/20 16 6:45 AM**	**8/3/201 6 1:30 PM**	**9366.75**	**10381. 5**				**extern al Shutdo wn**	**Mechan ical**
.	**8/3/201 6 11:15 PM**	**9/3/201 6 7:30 AM**	**10391.2 5**	**10399. 5**	**Trip by signal vacum**				**Mechan ical**
.	**9/3/201 6 10:45 PM**	**8/4/201 6 8:30 AM**	**10414.7 5**	**11120. 5**	**Trip by signal vacum**				**Mechan ical**
.	**8/4/201 6 9:30**	**9/4/201 6 1:15**	**11121.5**	**11137. 25**				**extern al**	**Mechan ical**

	AM	AM						Shutdown	
	22/5/2016 3:45 AM	6/6/2016 10:30 AM	12171.75	12538.5		De-excitation			Electrical
	6/6/2016 11:30 AM	4/8/2016 10:30 PM	12539.5	13966.5	Clean condenser				Mechanical
	5/8/2016 10:15 AM	13/8/2016 12:30 PM	13978.25	14172.5	Trip by signal vacum				Mechanical
	13/8/2016 1:30 PM	16/8/2016 8:45 AM	14173.5	14240.75		De-excitation			Electrical
	16/8/2016 9:30 AM	4/9/2016 11:30 PM	14241.5	14711.5	Clean condenser				Mechanical
	5/9/2016 1:15 PM	9/9/2016 8:30 AM	14725.25	14816.5		De-excitation			Mechanical
	9/9/2016 9:30 AM	30/9/2016 10:00 PM	14817.5	15334		Clean condenser			Mechanical
	2/10/2016 2:30 AM	5/10/2016 4:30 PM	15362.5	15448.5		De-excitation			Mechanical
	5/10/2016 5:15 PM	29/10/2016 11:30 PM	15449.25	16031.5		Clean condenser			Mechanical
	30/10/2016 8:00 AM	30/10/2016 2:15 PM	16040	16046.25			Low vacuum		Mechanical
	30/10/2016 2:45 PM	23/11/2016 3:15 PM	16046.75	16623.25		De-excitation			Mechanical
	23/11/2016	27/11/2016	16624.25	16714		De-excitati			Mechanical

	4:15 PM	**10:00 AM**				**on**			
	27/11/2016 12:45 PM	**12/12/2016 2:00 PM**	**16716.75**	**17078**		**High level in condenser**			**Mechanical**
	13/12/2016 7:45 PM	**14/12/2016 5:15 AM**	**17107.75**	**17117.25**			**High vibration**		**Mechanical**
	14/12/2016 11:00 AM	**15/12/2016 12:00 AM**	**17123**	**17136**				**External Shout Down**	**Mechanical**
	30/1/2017 3:45 PM	**31/1/2017 3:45 AM**	**18255.75**	**18267.75**			**High vibration**		**Mechanical**
	31/1/2017 12:15 PM	**20/2/2017 12:30 PM**	**18276.25**	**18756.5**				**Leakage**	**Mechanical**
	21/2/2017 11:45 PM	**22/2/2017 10:15 AM**	**18791.75**	**18802.25**			**High vibration**		**Mechanical**
	23/2/2017 10:00 AM	**17/3/2017 12:45 PM**	**18826**	**19356.75**				**Heavy leakage for drain line**	**Mechanical**
	17/3/2017 11:15 PM	**20/3/2017 12:00 AM**	**19367.25**	**19416**				**Air heater steam**	**Mechanical**
	21/3/2017 6:15 PM	**6/5/2017 10:30 PM**	**19458.25**	**20566.5**	**Clean condeser**				**Mechanical**
	7/5/2017 5:30 AM	**10/5/2017 5:00 PM**	**20573.5**	**20657**		**Execution in voltage starter**			**Electrical**

.	11/5/2017 4:15 AM	11/5/2017 4:45 PM	20668.25	20680.75		De-excitation			Mechanical
.	11/5/2017 5:30 PM	14/6/2017 5:30 PM	20681.5	21497.5		De-excitation			Mechanical
.	14/6/2017 7:30 PM	14/6/2017 8:15 PM	21499.5	21500.25		De-excitation			Mechanical
.	14/6/2017 9:15 PM	6/7/2017 12:00 AM	21501.25	22008				Leakage	Mechanical
.	11/7/2017 5:00 AM	9/8/2017 10:30 AM	22133	22834.5			Low vacuum		Mechanical
.	9/8/2017 12:45 PM	10/8/2017 2:30 PM	22836.75	22862.5		De-excitation			Mechanical
.	10/8/2017 3:30 PM	10/8/2017 4:30 PM	22863.5	22864.5		De-excitation			Mechanical
55.	10/8/2017 6:15 PM	13/8/2017 12:45 AM	22866.25	22920.75		De-excitation			Mechanical
56.	15/8/2017 1:15 PM	26/8/2017 11:30 PM	22981.25	23255.5				Leakage	Mechanical
57.	28/8/2017 8:30 PM	17/10/2017 9:15 AM	23300.5	24489.25			Low vacuum		Mechanical
58.	18/10/2017 1:15 AM	19/10/2017 3:45 AM	24505.25	24531.75				Drum level high	Mechanical
59.	19/10/2017 12:00 PM	22/10/2017 5:45 PM	24540	24617.75		De-excitation			Mechanical

60.	**22/10/2017 7:45 PM**	**1/11/2017 11:00 AM**	**24619.75**	**24851**				**Trip in 380V Circuit break**	**Electrical**
61.	**1/11/2017 2:15 PM**	**8/11/2017 12:15 AM**	**24854.25**	**25008.25**				**Leakage**	**Mechanical**
62.	**8/11/2017 9:00 PM**	**12/11/2017 9:30 PM**	**25029**	**25125.5**				**Loss both F.D.F**	**Mechanical**
63.	**13/11/2017 5:30 AM**	**18/11/2017 1:00 PM**	**25133.5**	**25261**		**Signal IPS logic**			**Control**
64.	**18/11/2017 1:30 PM**	**8/12/2017 12:00 AM**	**25261.5**	**25728**				**Wash air heater**	**Mechanical**
.	**10/12/2017 21:45**	**29/01/2018**	**25797.75**	**26976.00**				**Wash both side heater**	**Mechanical**
.	**29/01/2018 00:45**	**14/02/2018 22:00**	**26976.75**	**27382.00**		**De-excitation**			**Mechanical**
.	**14/02/2018 23:00**	**28/03/2018 08:00**	**27383.00**	**28376.00**				**Leakage**	**Mechanical**
.	**02/05/2018 08:00**	**06/05/2018 02:45**	**29216.00**	**29306.75**			**Low vacuum**		**Mechanical**
.	**06/05/2018 23:45**	**12/05/2018 21:30**	**29327.75**	**29469.50**		**Execution in voltage starter**			**Electrical**
.	**17/05/2018 06:00**	**12/06/2018 11:45**	**29574.00**	**30203.75**		**over current**			**Electrical**
.	**12/06/2018**	**03/08/2018**	**30211.50**	**31458.00**		**De-excitati**			**Mechanical**

	19:30	18:00				on			
	03/08/2018 19:15	11/08/2018 04:45	31459.25	31636.75		High level in condenser			Mechanical
	11/08/2018 22:00	28/08/2018 14:45	31654.00	32054.75				Drum level high	Mechanical
	28/08/2018 16:45	22/09/2018 08:45	32056.75	32648.75				Heavy leakage for drain line	Mechanical
	23/09/2018 12:45	23/09/2018 13:30	32676.75	32677.50		signal under voltage			Electrical
	23/09/2018 15:15	30/09/2018 05:00	32679.25	32837.00		De-excitation			Mechanical
	03/10/2018 04:15	04/10/2018 02:00	32908.25	32930.00				Heavy leakage for drain line	Mechanical
	04/10/2018 16:00	13/10/2018 05:30	32944.00	33149.50		De-excitation			Mechanical
	13/10/2018 09:30	16/10/2018 04:45	33153.50	33220.75		De-excitation			Mechanical
	17/10/2018 04:45	24/10/2018 23:00	33244.75	33431.00		De-excitation			Mechanical
	25/10/2018 16:45	25/10/2018 22:30	33448.75	33454.50				Trip by signal (lose of both F.D.F G.R.F	Mechanical
	25/10/2018 23:00	21/11/2018 12:15	33455.00	34092.25			Low vacuum		Mechanical

.	21/11/2018 14:15	23/12/2018 01:00	34094.25	34849.00				Trip in 380V Circuit break of fuel	Electrical
.	23/12/2018 09:00	01/01/2019 00:00	34857.00	35064	NO Failure until end 2018				

III. Methodology

The data collected for the electric power generation unit under study is shown in table 1, the 84 system failures of four years, when scanning the collected data, the failure was in the boiler (24), turbine (17), Generator (34), and the condenser (9). This data was entered using Matlab to generate a default matrix called the target matrix which is the main matrix by which the malfunctions are estimated, the size of the matrix depends on the largest number of failure occurrences and the types of failure in each sub-system. This means that the matrix is under study (35x12), table 2 illustrates the method of constructing the target matrix.

The total number of hours during this period is (4 years x 365 days) = 35064 hours, this period is divided by (34) is the largest number of failures (failure becomes between one period and another approximately 1031.3 hours), to get 35 equal time periods first start From (0) hours and the last ending with (35064) hours, as shown in the first column of the target matrix, table 3 . The number (1) means that a failure has occurred in the place indicated within the time period, the type of failure of the subsystem, while a number (0) means no failure has occurred in the same period, built digital matrix (0,1) .

Using the Matlab Software - Artificial Neural Networks - fitting net neural command, the data are entered into the target matrix to generate a neural network used for prediction, where the input parameters are time interval values, and the output parameters are the type of failure Digital code consists of 12 numbers as previously explained. Fig.2 shows the structure type of the (ANN) used in the search, it consists of an input layer that contains one neuron representing the time of failure, a hidden layer containing 100 neurons, and an output layer of eight neurons representing 12 exits of the type of failure and its location, the figure also shows the type of function used for each layer, full connection of neurons in all layers. The network trained on (90 %) of the data entered, (5 %) for testing, and (5 %) for valuation. The (ANN) shown in Fig. 2, by using eq. 1 the value of the MSE was calculated (6.54 E-16),and the regression (91%) after its training, Fig.3 shown the training, test ,and validation, for the purpose of using it to estimate the type of failure in the future.

$$\text{MSE} = \frac{1}{n}\sum_i^n (h_i - h_m)^2 \quad (1)$$

Where $h_i \& h_m$ the real and forecasted output value.

The output matrix and test after network training is shown in table 4 for year data (2015-2018), fig. 4 shows the amount of congruence of the target matrix with the output matrix. The (ANN) can be adopted to estimate the types of failures for the following years.

Table 4 shows the results of the estimation of the type of failure and its location in the subsystems of the production unit under study for the year 2019, when entering cumulative times for every 100 working hours. The estimation of the type of failure and its location in the sub-systems for the year 2020 is shown in table 5.

IV. Results and Discussion

- The system is under study of the type of continuous flow production, that is, it is supposed to work (24) hours throughout its service period. The process of scheduling, preventive maintenance for this type is difficult, as well as sudden maintenance. Because the subsystems have a series connected in a row as shown in fig. 1 this system is connected in parallel with similar systems, thus facilitating the maintenance process and keeping the production going. Table 1 shows the data collected to present the methodology of estimating the type of failure, which is very important and every production institution must document from the moment of operation of its production systems, in order to give a better accuracy of the reality of its operation, as the data size was greater and comprehensive, the results of the methodology for forecasting were better and closer to Reality.

- The number of failures in the system under study is very large at a rate of 21 times per year, and such systems require time to suspend, maintain, and operate longitudinally, estimated at a number of days to assume a week in the event that the necessary spare parts are available to maintain the failure, meaning that they leave the service by up to 40%. Therefore, care must be taken in reducing these times by scheduling their preventive maintenance for the recurring parts that fail, and merging the maintenance times of the other parts together, thus reducing the times of leaving the service.

- The failure rates in the sub-systems differed depending on the type and components of the sub-system. The highest percentage was in the generator (40.5%) with a failure number of the years under study (34), followed by the boiler by (28.5%), then the turbine (20.3%), and the last condenser (10.7%). So the generator is the ruling part in determining the number of rows in the input system for the neural network program to determine the appropriate network type for data, which is illustrated by the tables (2 and 3).

- Fig. 2 shows the network that was adopted to estimate the type of failure after its training, where during the training it reached the lowest (MSE), and the best regression rate for the data as shown in Fig.3, of the program used. Conformance results were good after re-entering the same times into the network and shown in table 4. This ANN, was adopted to estimate the type of failure of the sub-systems of the generation unit under study for the coming years.

- The network that adopted the data collected for the years (2015-2018) in estimating the type of failure for the year 2019,for every 10 days (240 hours), table (5) shows the results of the estimation in the sub-systems of the generating unit, where the failure rate in the generator (33%), in the turbine (29%), in the boiler (21%),and condenser (17%),Fig. 5 show that, The percentage of conformity with the real reality of a type of failure and its location for the year 2019 was between (82 %-87%) for all the sub-systems of the unit.

The failure type ratios for the year 2020 for every 10 days are shown in the Fig 6 and table 5 where the ratios were (33%) for the generator, (23%) for the boiler, (31%) for the turbine, and (13%) for the condenser.

Table 2: The target matrix of the Matlab

Target											
Boiler			Turbine			Generator			Condenser		
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM

BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	BE	BM	TC	TE	TM	GC	GE	GM	CC	CE	CM
BC	**BE**	**BM**	**TC**	**TE**	**TM**	**GC**	**GE**	**GM**	**CC**	**CE**	**CM**

Table 3: Matrix of the real target

Time hr.	**Real Target**											
	Boiler			**Turbine**			**Generator**			**Condenser**		
	M	**E**	**C**	**M**	**E**	**C**	**M**	**E**	**C**	**M**	**E**	**C**
0	0	0	0	0	0	0	0	0	0	1	0	0
1031.294	0	0	0	0	0	0	0	0	0	0	0	0
2062.588	0	0	0	0	0	0	0	0	0	0	0	0
3093.882	0	0	0	0	0	1	0	0	0	0	0	0
4125.176	0	0	0	0	1	0	0	1	0	0	0	0
5156.471	0	0	0	0	1	0	0	1	0	0	0	0
6187.765	0	0	0	0	0	0	0	0	0	1	0	0
7219.059	0	0	0	0	1	0	0	0	0	1	0	0
8250.353	0	0	0	0	0	0	0	1	0	0	0	0
9281.647	0	0	0	0	1	0	0	0	0	0	0	0
10312.94	0	0	0	0	0	0	0	0	0	1	0	0
11344.24	0	1	0	0	0	0	0	1	0	0	0	0
12375.53	0	0	0	0	0	0	0	1	0	0	0	0
13406.82	0	0	0	0	0	0	0	1	0	1	0	0
14438.12	0	0	0	0	1	0	1	0	0	1	0	0
15469.41	0	0	0	0	1	0	1	0	0	0	0	0
16500.71	0	0	0	0	0	0	1	0	0	0	0	0
17532	0	0	0	0	0	0	0	0	0	0	0	0
18563.29	0	0	0	0	1	0	0	0	0	0	0	0
19594.59	0	0	0	0	1	0	0	0	0	1	0	0
20625.88	0	0	0	0	1	0	1	0	0	0	0	0
21657.18	0	0	0	0	1	0	0	0	0	0	0	0

22688.47	0	0	0	0	1	0	1	0	0	0	0	0
23719.76	0	0	0	0	1	0	1	0	0	0	0	0
24751.06	0	0	0	0	0	0	0	0	1	0	0	0
25782.35	0	0	0	0	0	0	0	0	0	0	0	0
26813.65	0	0	0	0	1	0	1	0	0	0	0	0
27844.94	0	0	0	0	1	1	0	1	0	1	0	0
28876.24	0	0	0	1	0	1	1	1	0	0	0	0
29907.53	0	0	0	0	0	0	0	1	0	0	0	0
30938.82	0	0	0	0	0	0	1	0	0	0	0	0
31970.12	0	0	0	0	0	0	1	0	0	0	0	0
33001.41	0	0	0	0	0	0	1	0	0	0	0	0
34032.71	0	0	0	0	0	0	0	0	0	0	0	0
35064	0	0	0	0	0	0	1	0	0	1	0	0

Where:

CM = **M**echanical failure in Condenser.

CE = **E**lectrical failure in **C**ondenser.

Cc = **C**ontrol failure in Condenser

GM = **M**echanical failure in **G**enerator.

GE = **E**lectrical failure in **G**enerator.

Gc = **C**ontrol failure in **G**enerator.

TM = **M**echanical failure in **T**urbine.

TE = **E**lectrical failure in **T**urbine.

Tc = **C**ontrol failure in **T**urbine.

BM = **M**echanical failure in **B**oiler

BE = **E**lectrical failure in **B**oiler.

Bc = **C**ontrol failure in **B**oiler.

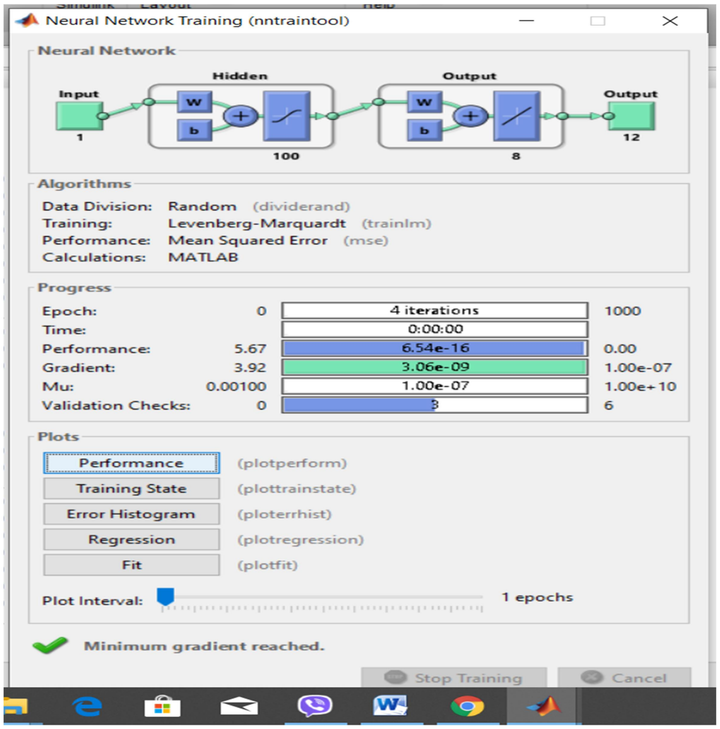

Fig. 2: The structure (ANN)

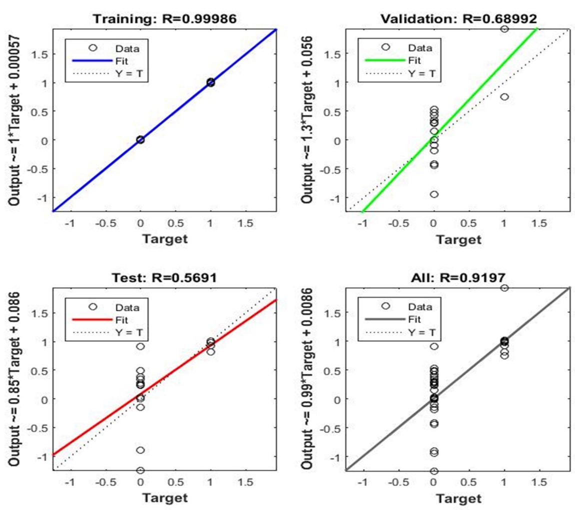

Fig. 3: The training, test, and validation

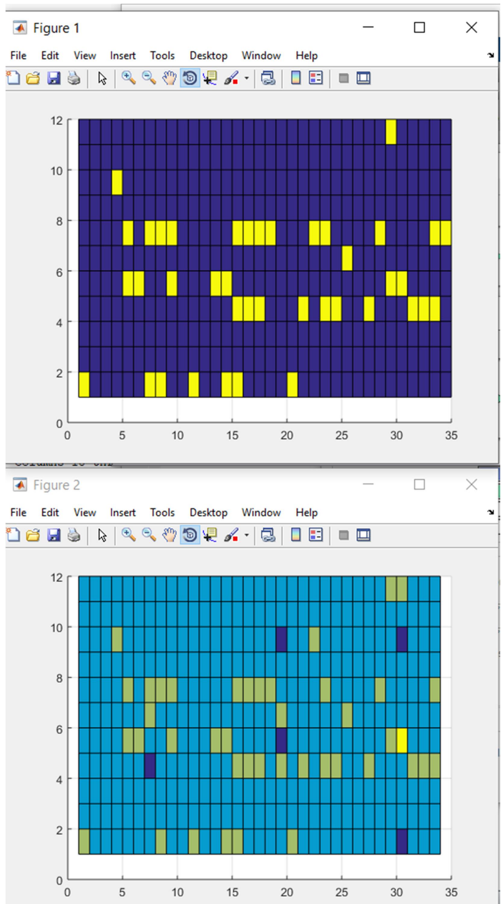

Fig. 4 the Approximate Results

Table 4: The Results of the estimated 2019

Time days	Condenser			Generator			Turbine			Boiler		
	M	**E**	**C**	**M**	**E**	**C**	**M**	**E**	**C**	**M**	**E**	**C**
10	0	0	1	0	0	0	0	0	0	0	0	0
20	0	0	0	0	1	0	0	0	0	0	0	0
30	0	0	0	0	0	0	0	0	0	0	0	0
30	0	0	0	0	0	0	1	0	0	0	0	0
40	0	0	0	0	0	0	0	0	1	1	0	0

50	0	0	0	1	0	0	0	0	0	1	0	0
60	1	0	0	0	0	0	0	0	0	0	0	0
70	0	1	0	0	0	0	1	0	0	1	0	0
80	0	0	0	0	0	0	0	0	1	0	0	0
90	0	0	0	0	0	0	0	0	0	1	0	0
100	1	0	0	0	0	0	0	0	0	0	0	0
110	0	0	0	1	0	0	0	0	0	1	0	0
120	0	0	0	1	0	0	0	0	0	0	0	0
130	1	0	0	0	0	0	0	0	0	0	0	0
140	0	0	0	1	0	0	1	0	0	0	0	0
150	0	0	0	1	0	0	1	0	0	1	0	0
160	0	0	0	0	0	1	0	0	0	0	0	0
170	1	0	0	0	0	0	1	0	0	0	0	0
180	0	0	0	0	0	0	0	0	0	0	0	0
190	0	0	0	0	0	0	0	0	0	0	0	0
200	1	0	0	0	0	0	0	0	0	0	0	0
210	0	0	0	0	0	1	0	0	0	1	0	0
220	0	0	0	0	0	0	1	0	0	0	0	0
230	1	0	0	0	0	0	0	0	0	1	0	0
240	0	0	0	1	0	0	0	0	0	0	0	0
250	1	0	0	0	0	0	0	0	0	0	0	0
260	0	0	0	0	0	0	0	0	0	0	0	0
270	0	0	0	1	0	0	0	0	0	0	0	0
280	0	0	0	0	0	0	1	0	0	0	0	0
290	0	0	0	0	0	0	0	0	0	0	0	0

300	0	0	0	0	0	0	1	0	0	0	0	0
310	0	0	0	1	0	0	0	0	0	0	0	0
320	0	0	0	0	0	0	0	0	0	0	0	0
330	0	0	0	1	0	0	0	0	0	0	0	0
340	0	0	0	0	0	0	1	0	0	0	0	0
350	1	0	0	0	0	0	1	0	0	0	0	0
360	0	0	0	0	0	0	0	1	0	0	0	0
365	0	0	0	1	0	0	1	1	0	0	0	0

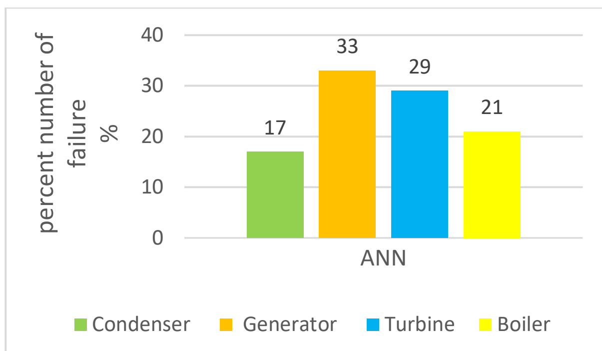

Fig. 5: The estimated failure type for (2019)

Table 5: The results of the estimated 2020

Time days	**Condenser**			**Generator**			**Turbine**			**Boiler**		
	M	**E**	**C**	**M**	**E**	**C**	**M**	**E**	**C**	**M**	**E**	**C**
10	0	0	0	0	0	0	0	0	0	0	0	1
20	0	0	0	0	0	0	0	1	0	0	0	0
30	0	0	0	0	0	0	0	0	0	0	0	0
30	0	0	0	1	0	0	0	0	0	0	0	0
40	1	0	0	0	0	1	0	0	0	0	1	0

50	0	0	0	0	0	0	1	0	0	0	0	0
60	0	0	0	0	0	0	0	0	0	1	0	0
70	1	0	0	1	0	0	0	0	0	0	0	0
80	0	0	0	0	0	1	0	0	0	0	0	0
90	1	0	0	0	0	0	0	0	0	1	0	0
100	0	0	0	1	0	0	0	0	0	0	0	0
110	1	0	0	0	0	0	1	0	0	0	0	0
120	0	0	0	0	0	0	1	0	0	0	0	0
130	0	0	0	0	0	0	0	0	0	1	0	0
140	0	0	0	1	0	0	1	0	0	0	0	0
150	1	0	0	1	0	0	1	0	0	0	0	0
160	0	0	0	1	0	0	0	0	1	0	0	0
170	0	0	0	1	0	0	0	0	0	1	0	0
180	0	0	0	0	0	0	0	0	0	0	0	0
190	0	0	0	1	0	0	0	0	0	1	0	0
200	0	0	0	0	0	0	0	0	1	0	0	0
210	0	0	0	1	0	0	0	0	0	0	0	0
220	1	0	0	0	0	0	0	0	0	1	0	0
230	0	0	0	0	0	0	0	0	0	0	0	0
240	0	0	0	0	0	0	1	0	0	0	0	0
250	0	0	0	0	0	0	1	0	0	0	0	0
260	0	0	0	0	0	0	0	0	0	0	0	0
270	0	0	0	0	0	0	0	0	0	1	0	0
280	0	0	0	0	0	0	1	0	0	0	0	0
290	0	0	0	1	0	0	0	0	0	0	0	0

300	0	0	0	0	0	0	1	0	0	0	0	0
310	0	0	0	1	0	0	0	0	0	1	0	0
320	0	0	0	0	0	0	1	0	0	0	0	0
330	0	0	0	0	0	0	0	0	0	1	0	0
340	0	0	0	1	0	0	0	0	0	0	0	0
350	0	0	0	0	1	0	0	0	0	0	0	0
360	0	0	0	0	0	0	1	0	0	0	0	0
366	0	0	0	1	0	0	1	0	0	0	0	0

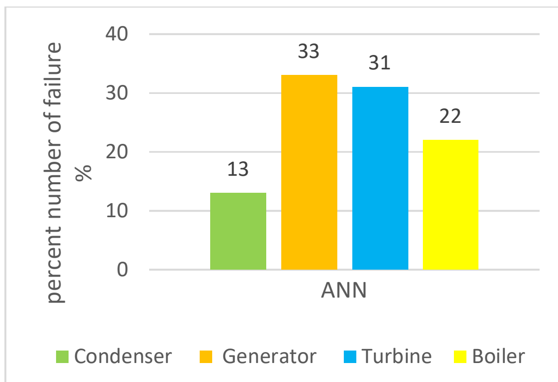

Fig. 6: the estimated failure type for (2020)

V. Conclusions

- The methodology proposed in this paper yielded results that match with the data used in it, and high affinity ratios (82%-87%) with the following year. This percentage can be increased by retraining the network by entering data for subsequent years that will improve weights between neurons in all layers of the network.

- Estimating the type of failure for future years, decision makers and professionals in the field of maintenance are happy with estimating times for preventive maintenance, setting the necessary plans to purchase spare parts, and interfering with maintenance plans and their timing. Thus, it will reduce downtime and reduce costs.

- The proposed methodology was applied here to the flow production system. It can be applied to other types of production such as batch production, mass production, and others.

- The higher the size and accuracy of data, the more accurate the estimate for this type of (ANN), because it requires a large amount of data. Therefore, it is necessary for institutions to document operating and stopping data, type of failure, maintenance teams, materials needed, and purchase prices.

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