Prediction of Gas Turbine Blade Lifetime Using Artificial Neural Network

Nurcahyo Herwin Dewanto[1], Suwarno[2]

Abstract*—Turbine blade is a critical component in a gas turbine that converts combustion energy into electricity. Due to its high temperature and pressure operation, maintenance of this component is crucial. The manufacturer normally has guidance of maintenance, i.e. different type of maintenance scheme is performed so-called A-B-A-C scheme which is performed every 6,000 equivalent operation hour (EOH). In A and B type inspection, visual inspection is done to turbine blade, and monitoring in next inspection is done if damages found. Turbine blade is replaced at C-Inspection (24,000 EOH) due to availability of power plant. The first stage turbine blade is made of nickel-based superalloy, and damages like missing material, crack, hole, coating spallation found during inspection. Accurate life prediction is need to ensure safety of gas turbine operations. In this paper lifetime prediction using ANN (Artificial Neural Network) used to predict the lifetime of gas turbine blade 145 MW Muara Tawar Power Plant. For input variable we use operation data and for target we use the amount of defect. After several times of training and testing show that network model with 8 inputs, 20 neurons, and 7 targets with MSE (Mean Square Error) 5.42E-02 and R (Regression) 9.85E-01 is able to predict defect as consideration that lifetime of turbine blade will reach one operation cycle.

***Keywords*—Turbine Blade, Defect, Prediction, Lifetime, ANN.**

I. INTRODUCTION

Gas turbine is main equipment in power plant that convert hot gas from combustion as mechanic energy to drive the generator producing electricity. Failure of gas turbine has tremendous effect to power plant performance. Muara Tawar Power Plant has five units gas turbine with capacity 145 MW. For unit 1 to 3 (called GT 11, GT 12, GT 13) operated in combined cycle and the others (GT 21 and GT 22) operated in open cycle. The gas turbine consist of 21 stages compressor dan 5 stages turbine. Turbine blade (rotary part) is critical component in gas turbine, which operating in high temperature and pressure. The material of turbine blade is precipitation-hardened Ni based super alloy. The gas turbine has maintenance interval 6,000 EOH (Equivalent Operation Hour) called A-B-A-C Inspections (Figure1). During A-Inspections, there is no scheduled replacement of hot-gas-path parts, including combustor, liners and turbine parts. The unit does not need to be disassembled for the A- and B-Inspection. It is possible to inspect the blading via borescope inspection holes. Although the information gained from A- and B-Inspections and from analysis of operating data is usually sufficient to assess the potential conditions, unexpected findings during the next visual inspection could lead to required corrective actions. Adequate spare parts should be made available to cover such eventualities. The manufacture has provided document for guideline which can be used during A- and B-Inspections to evaluate potential defects found on turbine airfoils (Figure 2), and to make judgements about the suitability for further operation. The recommendations were formulated according to best available knowledge and are based on design analysis, laboratory investigations of blade samples, and current fleet experience.

In GT 22 first maintenance interval (6,000 EOH) found that almost all blades have defect coating spallation. According to acceptance criteria it is safe to run to unit till next inspection. At next inspection (B-Inspection) found that the amount of blade with coating spallation is increasing. Between B-Inspection and next A-Inspection there were work in combustor area to inspect burner condition. The inspection access is from combustor manhole so we also could inspect turbine blade row 1. The inspection result give new data that other defect such as missing leading edge and trailing edge (Figure 3 and 4), hole at leading edge (Figure 5), crack at leading edge (Figure 6) found in several blades.

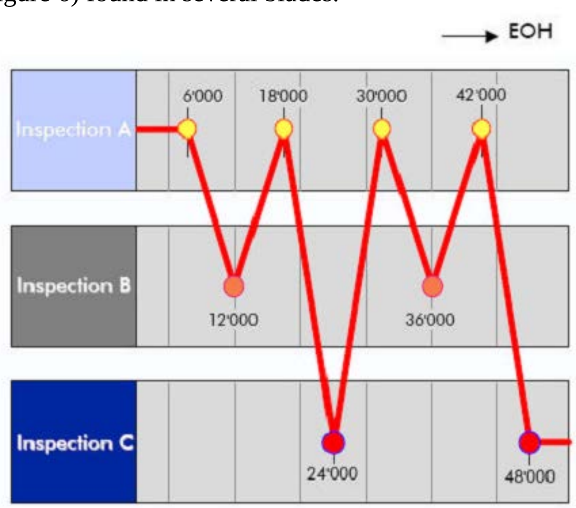

Figure 1. Maintenance interval

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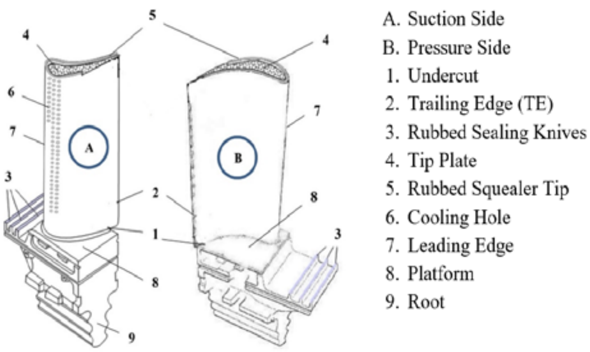

Figure 2. Turbine Blade Row 1 Airfoil.

Figure 3. Missing Leading Edge.

Figure 4. Missing Trailing Edge

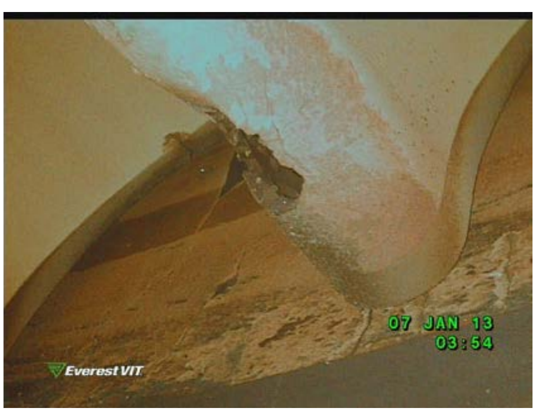

Figure 5. Hole at Leading Edge

Figure 6. Crack at Leading Edge

It was decided to reduce maintenance interval to 3,000 EOH. During next inspection found that the number of defect increase as the increasing of EOH. Accurate life prediction is need to ensure safety of gas turbine operations. Each component in the power plant requires non-destructive evaluation and further analyses based on the results obtained from the NDE [1]. In this condition only visual inspection can be done by borescope from inspection holes. We need to predict what defect in next inspection to ensure the gas turbine can reach the operation cycle (24,000 EOH) based on defects as decision to continue safe operations.

ANNs are employed in many areas of industry such as power system, robotics, controls, medicine. Their learning and generalization capabilities make them highly desirable solutions for complex problems. ANNs are considered to be a powerful data modeling tool as it can capture and implicitly represent complex relationships with many variables, such as the input/output variables [2].

II. Method

A two-layer feed-forward network with sigmoid hidden neurons and linier output neurons (fitnet) (Figure 7) is used to design the network model. The network will be trained with Lavenberg-Marquardt backpropagation algorithm (trainlm). MSE (Mean Square Error) and regression analysis are used to evaluate its performance. MSE is the average squared difference between ouputs and targets. Lower values are better. Zero means no error. Regression R Values measure correlation between outputs and targets. An R value of 1 means a close relationship, 0 a random relationship. For input variable we use operation data and for target we use the amount of defect (Table 1). The data is taken from 2011 to 2014 from operation data/operator log-sheet (Table 2) and defect found during inspection of GT 22.

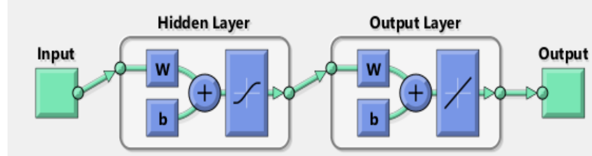

Figure 1. Network Model

From 232 samples, 162 samples for training, 35 samples for validation, and 35 samples for testing. The neuron is set 10 and 20 to get the best performance. For this network model 0.93 is the minimal value of R. MATLAB R2018a software is used to train the network.

TABLE 1.
INPUTS AND TARGETS VARIABLE

INPUTS		TARGETS	
x1 :	EOH (Equivalent Operation Hour)	t1 :	Coating spallation
x2 :	S (Starrt)	t2 :	Missing trailing edge at top position
x3 :	PLS (Protective Load Shedding	t3 :	Missing leading edge at top position
x4 :	T (Trip)	t4 :	Cracks at hole in platform area
x5 :	LR (Load Rejection)	t5 :	Crack at trailing edge
x6 :	UA (Unit Abort)	t6 :	Crack at leading edge
x7 :	EL (Emergency Load)	t7 :	Hole at leading edge
x8 :	TH (Trip High)		

TABLE 2.
OPERATION DATA FOR INPUTS VARIABLE

No	x1	x2	x3	x4	x5	x6	x7	x8
	EOH	S	PLS	T	LR	UA	EL	TH
1	11750	1406	96	26	4	243	0	8
2	11785	1407	96	26	4	243	0	8
3	1183	1408	96	26	4	243	0	8
…	…	…	…	…	…	…	…	…
21	12809	1428	96	27	4	248	0	9
…	…	…	…	…	…	…	…	…
36	13829	1443	101	27	4	248	0	9
…	…	…	…	…	…	…	…	…
172	19768	1582	106	28	4	256	0	10
…	…	…	…	…	…	…	…	…
232	22009	1644	110	28	4	272	0	10

III. RESULTS AND DISCUSSION

It is show that the best performance is 8-20-7 at epoch 102 with MSE 5.42E-02 and R 9.85-01 (Table 3).

The network model is checked by applying it to other unit. In this case we use GT 11. The network model simulation shows good result with MSE 1.55E-01 and R 9.88E-01 (Table 4) with best performance is 0.01751 at epoch 208 (Figure 10) and Regression 0.99975 (Figure 11).

Based on network model we want to predict the defect in GT 22 from 17,000 to 22,000 EOH. Table 5 shows the sample result of defect prediction.

Table 5 shows that network is able to predict defect. The results of prediction is used for guidance to decide gas turbine running operation. At 18,000 EOH is predicted that the number of defect coating spallation (t_1) and missing leading edge (t_3) increases. Finally, at 22,000 EOH the number of defect coating spallation (t_1), missing leading edge (t_3), cracks at leading edge (t_6), hole at leading edge (t_7) increases. The defects are accepted according acceptance criteria so we can decide that the gas turbine is safe to operate until the end of one cycle.

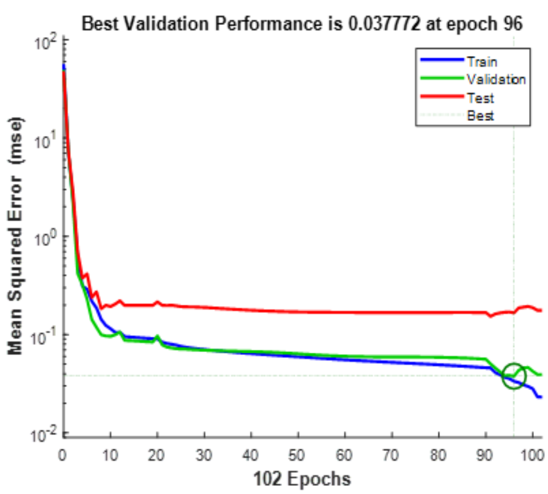

Figure 2. Performance at 102 epochs

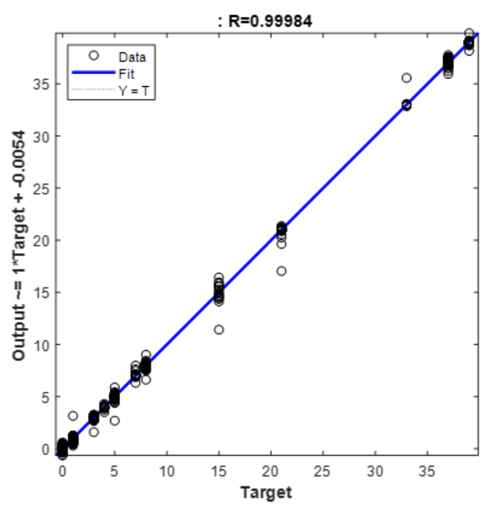

Figure 3. Regression at 102 epochs

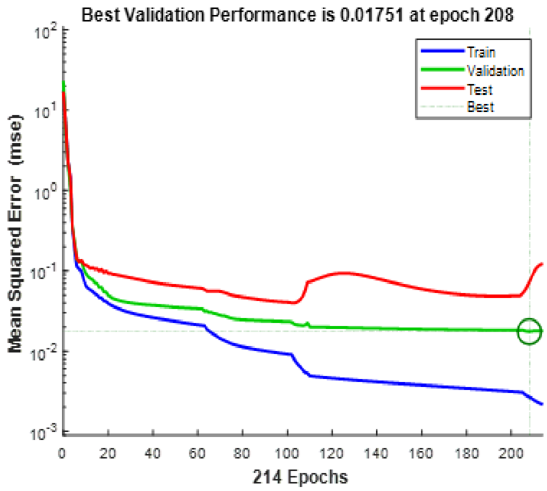

Figure 4. Performance at 214 epochs

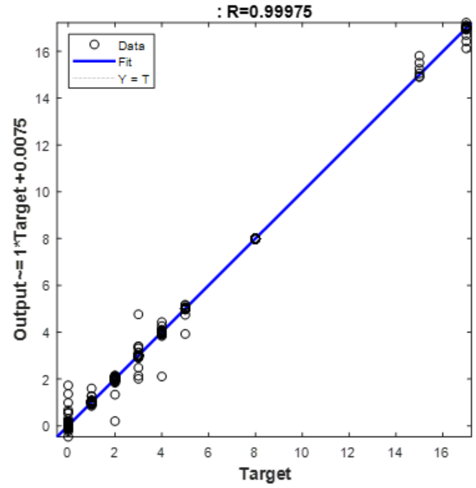

Figure 5. Regression at 214 epochs

TABLE 3.
RESULTS OF NETWORK TRAINING AND TESTING

Architecture	Epoch	Time	MSE Training	R Training	MSE Training	R Testing
8-10-7	110	00:00:15	9.96E-02	9.90E-01	1.18E-01	9.59E-01
8-10-7	31	00:00:04	1.71E-01	1.50E-01	1.72E-01	9.60E-01
8-10-7	63	00:00:08	1.33E-01	9.99E-01	1.37E-01	9.70E-01
8-10-7	52	00:00:06	6.10E-02	9.99E-01	1.26E-01	9.60E-01
8-10-7	160	00:00:21	9.69E-03	9.99E-01	6.70E-02	9.86E-01
8-20-7	93	00:00:12	8.20E-02	9.99E-01	1.10E-01	9.71E-01
8-20-7	81	00:00:11	1.05E-01	9.99E-01	1.04E-01	9.81E-01
8-20-7	102	00:00:13	3.35E-02	9.99E-01	5.42E-02	9.85E-01

TABLE 4.
RESULT OF NETWORK TRAINING AND TESTING FOR GT 11

Epoch	Time	MSE Training	R Training	MSE Training	R Testing
131	00:00:30	1.73E-02	9.99E-01	7.76E-02	9.76E-01
214	00:00:31	2.68E-03	1.75E-02	1.55E-02	9.88E-01
114	00:00:16	1.31E-01	4.40E-02	2.33E-02	9.83E-01
142	00:00:20	6.18E-03	9.99E-01	1.28E-02	9.88E-01
123	00:00:17	7.94E-03	9.99E-01	1.09E-02	9.90E-01

IV. CONCLUSION

Defect at turbine blade found at first maintenance interval (6,000 EOH) and the number increase as EOH, Start, Trip, PLS (Protective Load Shedding), LR (Load Rejection), EL (Emergency Load), TH (Trip High Temperature). Network training and testing 8-20-7 with epoch 102, MSE 5.42E-02, and R 9.85E-01. Network model is able to predict defect until one cycle operation.

In the future, input variable also include fuel composition because sulphur contain will reduce the bonding of thermal barrier coating at turbine blade become coating spallation.

ACKNOWLEGMENTS

Author gratefully acknowledge PT Pembangkitan Jawa Bali and Institut Teknologi Sepuluh Nopember for adequate support and providing technical information regarding this study.

TABLE 5.
DEFECT PREDICTION IN GT 22

EOH	t1		t2		t3		t4		t5		t6		t7	
	Pred.	Aktu.	Pred.	Aktu.	Pred.	Aktu.	Pred.	Aktu.	Pred.	Aktu.	Pred.	Aktu.	Pred.	Aktu.
17365	36.86	37	1	1	5.20	5	-0.041	0	-0.008	0	7.97	8	2.89	3
17394	36.85	37	1	1	5.21	5	-0.043	0	-0.012	0	7.99	8	2.89	3
17428	36.85	37	1	1	5.20	5	-0.041	0	-0.011	0	7.99	8	2.89	3
17523	37.06	37	1	1	5.29	5	-0.020	0	-0.027	0	8.18	8	2.94	3
17583	37.06	37	1	1	5.28	5	-0.020	0	-0.023	0	8.16	8	2.94	3
17619	37.06	37	1	1	5.27	5	-0.020	0	-0.020	0	8.15	8	2.94	3
17744	37.06	37	1	1	5.26	5	-0.019	0	-0.008	0	8.11	8	2.94	3
17868	37.44	37	1	1	5.53	5	-0.007	0	-0.027	0	8.20	8	2.97	3
18016	37.44	39	1	1	5.52	7	-0.007	0	-0.004	0	8.15	8	2.97	3
18156	38.10	39	1	1	6.12	7	0.001	0	-0.036	0	8.23	8	3.00	3
18261	39.05	39	1	1	6.90	7	0.007	0	-0.081	0	8.22	8	3.03	3
18398	39.03	39	1	1	6.89	7	0.016	0	-0.020	0	8.24	8	3.05	3
18979	39.07	39	1	1	7.30	7	-0.171	0	-0.118	0	8.13	8	2.91	3
19026	39.06	39	1	1	7.26	7	-0.176	0	-0.100	0	7.97	8	2.90	3
19107	39.05	39	1	1	7.21	7	-0.168	0	-0.081	0	7.96	8	2.92	3
19146	39.01	39	1	1	7.04	7	-0.250	0	0.023	0	6.54	8	2.76	3
19169	39.01	39	1	1	7.06	7	-0.224	0	0.013	0	6.92	8	2.81	3
19229	39.01	39	1	1	7.06	7	-0.186	0	0.009	0	7.42	8	2.89	3
19263	39.01	39	1	1	7.05	7	-0.170	0	0.012	0	7.61	8	2.92	3
19297	39.01	39	1	1	7.04	7	-0.154	0	0.015	0	7.80	8	2.95	3
19453	39.01	39	1	1	7.02	7	-0.033	0	0.008	0	9.35	8	3.19	3
19506	39.02	39	1	1	7.04	7	0.040	0	-0.009	0	10.34	8	3.33	3
19571	39.01	39	1	1	7.03	7	0.097	0	-0.010	0	11.06	8	3.44	3
19701	39.01	39	1	1	7.01	7	0.221	0	-0.010	0	12.62	15	3.68	4
19906	39.00	39	1	1	6.95	7	0.401	0	0.018	0	14.82	15	4.03	4
19968	38.99	39	1	1	6.95	7	0.471	0	0.022	0	15.73	15	4.17	4
20000	38.99	39	1	1	6.94	7	0.504	1	0.027	0	16.15	15	4.23	4
20034	38.99	39	1	1	6.93	7	0.533	1	0.036	0	16.50	15	4.29	4
20084	38.99	39	1	1	6.97	7	0.620	1	0.029	0	17.70	15	4.46	4
20108	39.00	39	1	1	6.98	7	0.664	1	0.026	0	18.30	15	4.54	4
20136	39.00	39	1	1	6.99	7	0.699	1	0.030	0	18.77	21	4.61	5
20179	39.01	39	1	1	7.04	7	0.787	1	0.022	0	20.03	21	4.78	5
20209	39.01	39	1	1	7.05	7	0.815	1	0.032	0	20.39	21	4.83	5
20242	39.01	39	1	1	7.04	7	0.836	1	0.049	0	20.66	21	4.88	5
20273	39.00	39	1	1	7.04	7	0.860	1	0.064	0	20.96	21	4.92	5
20337	39.00	39	1	1	7.04	7	0.900	1	0.099	0	21.47	21	5.00	5
20595	38.99	39	1	1	7.11	7	0.994	1	-0.162	0	21.06	21	5.04	5
20646	38.98	39	1	1	7.11	7	0.992	1	-0.127	0	21.00	21	5.04	5
20698	38.98	39	1	1	7.11	7	0.990	1	-0.090	0	20.94	21	5.03	5
20752	38.98	39	1	1	7.11	7	0.987	1	-0.051	0	20.87	21	5.03	5
20782	38.98	39	1	1	7.11	7	0.990	1	-0.020	0	20.89	21	5.04	5
20928	39.06	39	1	1	7.89	7	0.984	1	-0.052	0	21.09	21	4.95	5
20970	39.06	39	1	1	7.90	7	0.984	1	-0.011	0	21.07	21	4.95	5
21089	39.05	39	1	1	7.93	8	0.987	1	0.117	0	21.02	21	4.96	5
21113	39.04	39	1	1	7.94	8	0.991	1	0.156	0	21.04	21	4.96	5
21319	39.02	39	1	1	8.00	8	1.002	1	0.443	0	21.00	21	4.99	5
21378	39.01	39	1	1	8.02	8	1.007	1	0.543	1	21.01	21	5.00	5
21448	39.03	39	1	1	8.04	8	0.985	1	0.965	1	20.89	21	4.95	5
21517	39.01	39	1	1	8.02	8	1.005	1	0.980	1	21.03	21	4.99	5
21605	38.99	39	1	1	8.08	8	1.010	1	0.871	1	20.97	21	5.01	5
21634	38.98	39	1	1	8.10	8	1.013	1	0.926	1	20.97	21	5.02	5
21759	39.03	39	1	1	8.01	8	0.978	1	0.963	1	20.98	21	4.97	5
21781	39.02	39	1	1	8.01	8	0.981	1	1.000	1	20.98	21	4.98	5
21866	39.02	39	1	1	8.02	8	0.979	1	1.097	1	20.87	21	4.98	5
21931	38.98	39	1	1	8.00	8	1.018	1	1.015	1	20.95	21	5.02	5
21972	38.97	39	1	1	7.96	8	1.022	1	1.034	1	20.94	21	5.03	5
22009	38.97	39	1	1	7.94	8	1.021	1	1.050	1	20.88	21	5.03	5

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