AVAILABILITY AND PROFIT OPTIMIZATION OF CONTINUOUS CASTING SYSTEM OF THE STEEL INDUSTRY USING ARTIFICIAL NEURAL NETWORK TECHNIQUE

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Abstract

The main purpose of this study was to optimize the performance parameters of the casting process using a neural network approach. The casting process is molten or liquefied metal is poured into the mould cavity, after solidification it takes the near net shape of the cavity. The entire manufacturing process goes through six stations viz Pouring turret "ladle", "Tundish", "Mould", "Water spray chamber", "Support roller" and "Torch cutter". The Artificial Neural Network (ANN) technique is used in this paper to analyze the casting system's availability, profitability, and state probability variation. An effort has been made to identify the most critical component of the system. The outcomes of the analysis will help the practitioners in deciding effective maintenance strategies.

Keywords: Neural Network Approach, Neural weights, Profit, Availability

1. Introduction

The business sector must adopt the paths of quick technological progress to survive the current business climate. The absolute necessity for a corporation to survive is now massively automated systems. Many conventional industrial materials are finding it difficult to fulfill the demands of today's industries as industrial manufacturing technologies continue to advance. The manufacturers' primary focus is on the development of systems with lower development costs so that maximum profit may be gained, and they have succeeded in doing so to a significant extent by incorporating some performance improvement approaches into their systems. Even if such massive systems will eventually fail, the damage can be reduced by increasing their availability. Because of this, the availability of these systems has emerged as the most important factor in process industries. They can better comprehend the impact of variations in failure and repair rates of different subcomponents and units on the system by analyzing performance characteristics.
Tzong [1] emphasized improving cast parts availability and dependability while attempting to

minimize them as much as feasible. Agarwal and Bansal [2] use high-level repair specialties susceptible to shifting environmental circumstances to boost system dependability. Agarwal et al.[3] applied for cold standby redundancy in order to determine different reliability metrics. Bansal et al. [4] illustrate how to solve milk powder production facilities using the Boolean function technique and how mission phases affect the system's reliability. Amit Kumar [5] employed a probabilistic technique that helps the foundry plant's quality control departments increase production by minimizing cast component rejections, which raises dependability and lowers casting process costs. Agarwal and Bansal [6] examined the costs and dependability of a multi-component system, such as a thermal power plant, utilizing the supplemental variable technique to ensure the system's maximum dependability. Kumar [7] gives a thorough grasp of the casting industry to explore the several factors influencing the foundry industry's casting process and maximize casting quality, assuming adequate repair facilities are constantly accessible. Bansal [8] enhanced the availability of a repairable system by introducing the preemptive resume Repair Discipline. Bansal et al. [9] suggested an orthogonal matrix approach and the reliability was calculated when the exponential time distribution and Weibull were used to express the failure rate. Bansal and Tyagi [10] recognized the system's weak points so that suitable maintenance techniques can be implemented to strengthen the system's maintenance policy. Bansal et al. [11] Utilised the Markov Birth-Death Process, focusing on the leaf spring plant's performance to ascertain the system's availability. Chaudhari and Vasudevan [12] concentrated on creating a casting failure Markov chain model. It demonstrates how this predictive modeling technique may be used to produce the chance of casting failure through different casting faults and casting process parameters. Chaudhary and Bansal [13] offer improved standards for upcoming proposals and execution that will act as a basis for planning the expansion of hydroelectric power plant generation. Godara and Bansal [14] discussed the use of neural networks and Boolean functions as two separate methods for estimating the reliability of a steam turbine power facility. Tyagi and Bansal [15] resolved a water treatment plant using the Runge-Kutta technique, which aims to enhance the plant's operational performance by putting in place efficient maintenance practices. Godara and Bansal [16] examined the neural network approach's potential to improve the computer network system's dependability and profitability.
Recently, models based on artificial neural networks (ANN) have gained popularity for estimating system reliability. In this study, we develop a mathematical model of the casting industry using the Artificial Neural Network (ANN) technique. It has broad applicability in many areas, including dependability. The ANN is composed of microscopic units known as neurons, each of which has a distinct weight (synaptic strength) and is linked by synapses. We create neuron equations employing the neural weight in the mathematical model, and we assess the plant's dependability and performance with the aid of these equations. The applicability of different types of neural networks for probabilistic analysis needs to be thoroughly investigated these days. When using a neural network approach for analysis, all failure kinds and repair rates are treated as weights, and these weights are determined by the exponential distribution.

2. System Description

Continuous casting technology is a major advancement in the history of steelmaking and is influencing the worldwide steel industry. Globally, about 750 million tonnes of steel are produced annually, with continuous casting accounting for the majority of this solidification. The continuous casting method, seen in Figure 1, involves the flow of molten steel via a tundish and into the mould from a ladle. To protect each vessel from air exposure, a slag cover and ceramic nozzles should be positioned between each vessel. After entering the mould, the molten steel solidifies into a shell when it freezes up against the water-cooled copper walls. In order to maintain optimal operation in a steady state, the machine's driving rolls descend continuously, removing the shell from the mould at a rate known as the "casting speed" that corresponds to the flow of incoming metal. The remaining liquid is held in a container by the steel shell that is solidifying beneath the mould exit. Rolls are used to support steel to lessen ferrostatic pressure-induced bulging.

The strand's surface temperature is kept constant by air and water sprays until the molten core solidifies.

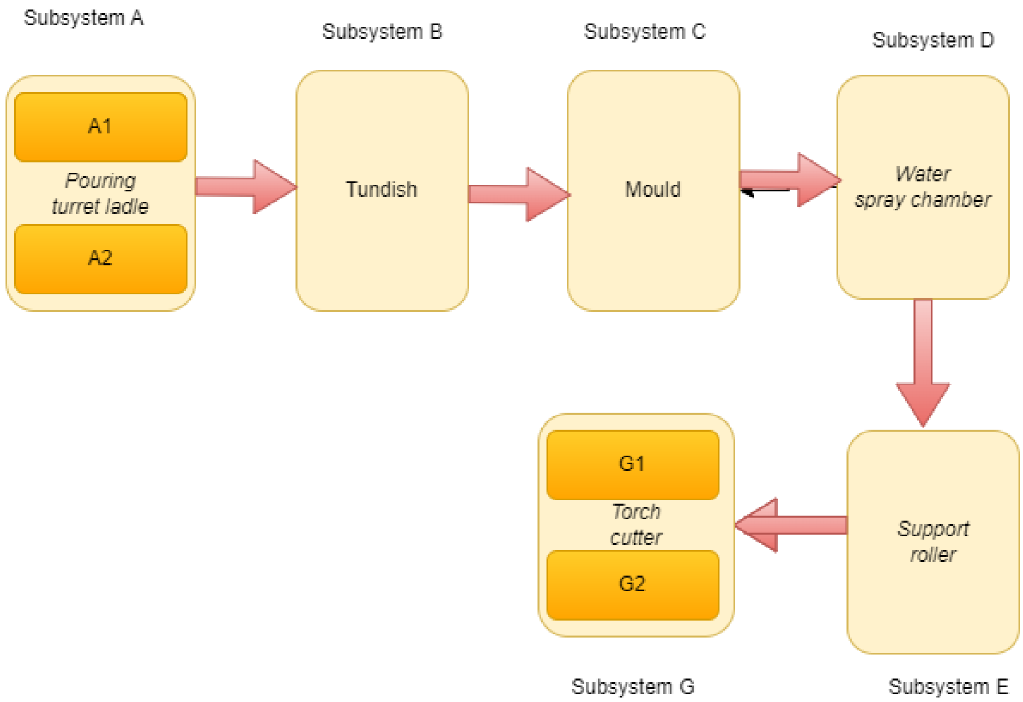

Figure 1: *Block diagram*

2.1. Assumptions and Notations

- First, we know the probabilities of the states.
- Every subsystem is initially in a fully operational state.
- Every subsystem has a repair facility in case it fails or deteriorates.
- There is a facility for repairs and the Repair rates are constant.
- Each subsystem's failure rate is both time-dependent and time-independent.

Moreover, the following notations are applied:

- f_{a1}/r_{a1} failure and repair rate of the 1st unit of turret ladle subsystem.
- f_{a2}/r_{a2} failure and repair rate of the standby unit of turret ladle subsystem.
- f_b/r_b failure and repair rate of the Tundish subsystem.
- f_c/r_c failure and repair rate of the Mould subsystem.
- f_d/r_d failure and repair rate of the Water spray chamber subsystem.
- f_e/r_e failure and repair rate of the Support roller subsystem.
- f_{g1}/r_{g1} failure and repair rate of the 1st unit of Torch cutter subsystem.
- f_{g2}/r_{g2} failure and repair rate of the standby unit of the Torch cutter subsystem.
- $w_{i,j}$ Neural weight of the ith state to the jth state.
- $P_i(t)$ Probability of the ith subsystem.
- A,B,C,D,E,G - Representation of the system is in a fully working state.
- a b c d e g Representation of the system is in the Failed state
- A^-, G^- Representation of the system is in the partially failed state.
- P_i is the probability that the system is in S_i state.

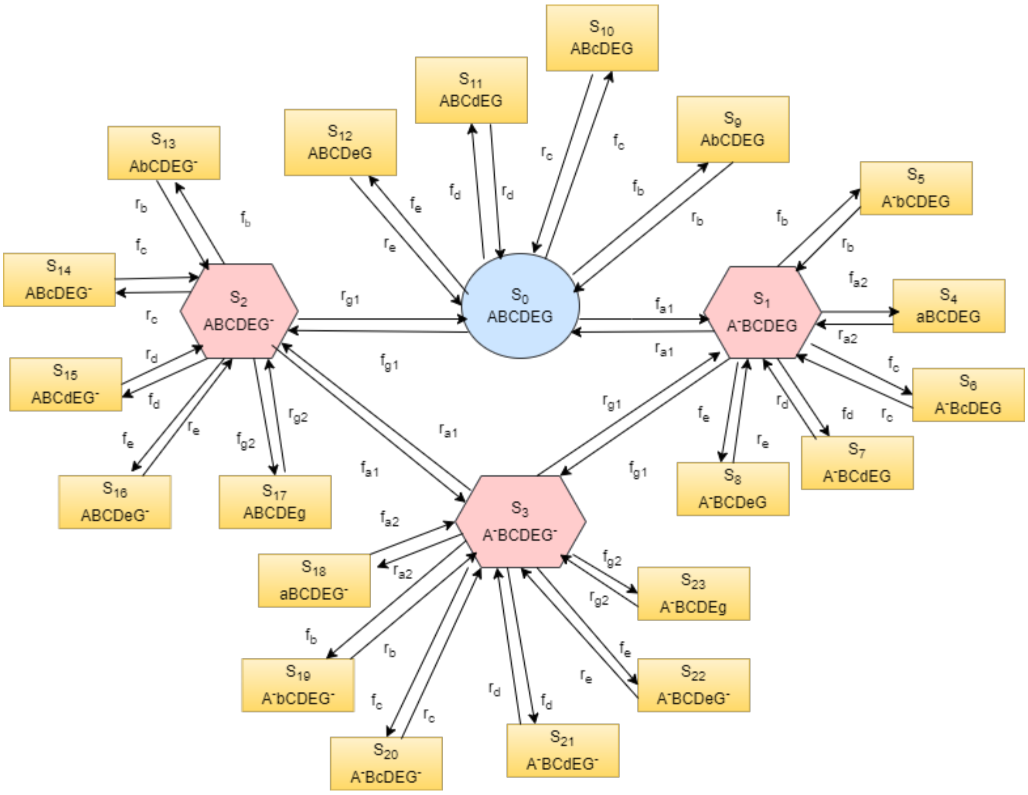

Figure 2: *State transition diagram*

2.2. Formulation of Artificial Neural Network Mathematical Model of the Continuous Casting System of the Steel Industry

The following set of difference differential equations governing the current mathematical model can be obtained using probability considerations and continuity arguments. There are three layers in the suggested ANN model: input, hidden, and output.

Input Layer. Input is defined by

$$P_i(t) = Z_i(t)$$

The following equations define the hidden layer:

$$P_0(t+\Delta t) = w_{0,0}Z_0 + w_{1,0}Z_1 + w_{2,0}Z_2 + w_{9,0}Z_9 + w_{10,0}Z_{10} + w_{11,0}Z_{11} + w_{12,0}Z_{12} \quad (1)$$

$$P_1(t+\Delta t) = w_{0,1}Z_0 + w_{1,1}Z_1 + w_{3,1}Z_3 + w_{4,1}Z_4 + w_{5,1}Z_5 + w_{6,1}Z_6 + w_{7,1}Z_7 + w_{8,1}Z_8 \quad (2)$$

$$P_2(t+\Delta t) = w_{0,2}Z_0 + w_{2,2}Z_2 + w_{3,2}Z_3 + w_{13,2}Z_{13} + w_{14,2}Z_{14} + w_{15,2}Z_{15} + w_{16,2}Z_{16} + w_{17,2}Z_{17} \quad (3)$$

$$P_3(t+\Delta t) = w_{1,3}Z_1 + w_{2,3}Z_2 + w_{3,3}Z_3 + w_{18,3}Z_{18} + w_{19,3}Z_{19} + w_{20,3}Z_{20} + w_{21,3}Z_{21} + w_{22,3}Z_{22} + w_{23,3}Z_{23} \quad (4)$$

$$P_4(t+\Delta t) = w_{1,4}Z_1 + w_{4,4}Z_4 \quad (5)$$

$$P_5(t+\Delta t) = w_{1,5}Z_1 + w_{5,5}Z_5 \quad (6)$$

$$P_6(t+\Delta t) = w_{1,6}Z_1 + w_{6,6}Z_6 \quad (7)$$

$$P_7(t+\Delta t) = w_{1,7}Z_1 + w_{7,7}Z_7 \quad (8)$$

$$P_8(t+\Delta t) = w_{1,8}Z_1 + w_{8,8}Z_8 \quad (9)$$

$$P_9(t+\Delta t) = w_{0,9}Z_0 + w_{9,9}Z_9 \quad (10)$$

$$P_{10}(t+\Delta t) = w_{0,10}Z_0 + w_{10,10}Z_{10} \quad (11)$$

$$P_{11}(t+\Delta t) = w_{0,11}Z_0 + w_{11,11}Z_{11} \tag{12}$$

$$P_{12}(t+\Delta t) = w_{0,12}Z_0 + w_{12,12}Z_{12} \tag{13}$$

$$P_{13}(t+\Delta t) = w_{2,13}Z_2 + w_{13,13}Z_{13} \tag{14}$$

$$P_{14}(t+\Delta t) = w_{2,14}Z_2 + w_{14,14}Z_{14} \tag{15}$$

$$P_{15}(t+\Delta t) = w_{2,15}Z_2 + w_{15,15}Z_{15} \tag{16}$$

$$P_{16}(t+\Delta t) = w_{2,16}Z_2 + w_{16,16}Z_{16} \tag{17}$$

$$P_{17}(t+\Delta t) = w_{2,17}Z_2 + w_{17,17}Z_{17} \tag{18}$$

$$P_{18}(t+\Delta t) = w_{2,18}Z_2 + w_{18,18}Z_{18} \tag{19}$$

$$P_{19}(t+\Delta t) = w_{3,19}Z_3 + w_{19,19}Z_{19} \tag{20}$$

$$P_{20}(t+\Delta t) = w_{3,20}Z_3 + w_{20,20}Z_{20} \tag{21}$$

$$P_{21}(t+\Delta t) = w_{3,21}Z_3 + w_{21,21}Z_{21} \tag{22}$$

$$P_{22}(t+\Delta t) = w_{3,22}Z_3 + w_{22,22}Z_{22} \tag{23}$$

$$P_{23}(t+\Delta t) = w_{3,23}Z_3 + w_{23,23}Z_{23} \tag{24}$$

Where

$$w_{0,0} = 1 - w_{0,1} - w_{0,2} - w_{0,9} - w_{0,10} - w_{0,11} - w_{0,12} \tag{25}$$

$$w_{1,1} = 1 - w_{1,0} - w_{1,5} - w_{1,3} - w_{1,4} - w_{1,6} - w_{1,7} - w_{1,8} \tag{26}$$

$$w_{2,2} = 1 - w_{2,0} - w_{2,3} - w_{2,13} - w_{2,14} - w_{2,15} - w_{2,16} - w_{2,17} \tag{27}$$

$$w_{3,3} = 1 - w_{3,2} - w_{3,1} - w_{3,18} - w_{3,19} - w_{3,18} - w_{3,19} - w_{3,20} - w_{3,21} - w_{3,22} - w_{3,23} \tag{28}$$

The output layer is defined by the following equation with the aid of the equation above.

$$Availability = P_0(t+\Delta t) + P_1(t+\Delta t) + P_2(t+\Delta t) + P_3(t+\Delta t) \tag{29}$$

3. Results and Discussions

In this section, we explore the estimated time-varying state probabilities as revealed by our analysis applied to the steel industry's continuous casting system. The utilization of the Artificial Neural Network (ANN) methodology has yielded valuable insights regarding the optimization of profit and availability of the system. The system's initial state probabilities are given in Table 1, and it is assumed that the system has been operating continuously.

Table 1: *Initial Probability of the System*

Probability	P_0	P_1	P_2	P_3	P_i,i= 4 to 23
Value	0.45	0.1	0.1	0.1	0.0125

Based on an analysis of Table 1, it can be observed that a good state has a higher probability than a failing or degraded state. Additionally, the initial probability of all failed states is 0.0125. When a system malfunctions, a repair facility is accessible because it is in three states: good, degraded, and failed.
Table 2 lists the repair rates for each subsystem.

Table 2: *Constant Repair Rate of the System*

Repair Rate	r_{a1}	r_{a2}	r_b	r_c	r_d	r_e	r_{g1}	r_{g2}
Value	0.2	0.2	0.1	0.1	0.1	0.1	0.2	0.2

The subsystem's failure rate is determined by the exponential and Weibull time distribution basis; there are two possible scenarios.
(1) Useful Life Phase: during this phase, the system's failure rate is constant and is distributed exponentially.
(2) Wear-out Phase: this phase is characterized by a Weibull time distribution that follows a time-dependent failure rate of the system.
In the Useful life Phase, the system's failure rate is constant and is distributed exponentially, and the wear-out phase is characterized by a Weibull time distribution that follows a time-dependent failure rate of the system. In the case of the wear-out phase, the failure rate of the system is calculated by equation.

$$f(t) = \beta t^{(\beta-1)} \eta^{\beta} \tag{30}$$

Where (β) and (η) represent the wear-out phase failure rate's shape and scale parameters, respectively. In order to match the starting failure rates of each subsystem and assume constant failure rates, the shape parameters (β) and scale parameters (η) of the time-dependent failure rates of each subsystem at time t = 0 have been taken as shown in Table 3.

Table 3: *Constant and Time-Dependent Failure Rate*

Failure rate	f_{a1}	f_{a2}	f_b	f_c	f_d	f_e	f_{g1}	f_{g2}
Shape Parameter(β)	2	2	2	2	2	2	2	2
Scale Parameter (η)	1.65	2.36	0.75	0.65	0.85	0.9	3	5
Time-dependent Failure rate	.0103	.050	.0498	0.066	0.033	0.034	0.031	0.011
Constant Failure rate	0.01	0.05	0.05	0.07	0.04	0.04	0.026	0.03

According to the ANN approach, the linear combination of the initial probability with the weight function and bias function is added to determine the state probability of any subsystem over time. To bring the estimated values of state probabilities closer to the measured state probabilities, bias is a constant that is added to the activation function in the described ANN model. Therefore, assuming b_j = 0 because measured state probabilities have not been taken into account in this numerical computation.
The ANN input layer of the casting system is determined by the initial probability of the system, which is given in Table 1. The hidden layer of the network is calculated with the help of equations 1 to 24, in which the neural weight of the system is calculated with the help of a linear combination of the failure and repair rate of the system, as shown in equations 25 to 28. The hidden layer of the ANN model shows the state probability of the system. The variation in the state probability of the system is calculated in both the cases namely useful life period phase and wear-out phase, these variations are calculated with a time increment of 10 hours. Here in this model, for the calculation purpose time, the factor is taken in month 10 hours= 0.014 month. The state probability fluctuates during the wear-out phase and the useful-life period, as Tables 4 to 9 demonstrate.

Table 4: *Change in State Probabilities With Time In Useful-Life Phase)*

T	P_0	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8
10	.4491	.0998	.0999	.0992	.0125	.0126	.0126	.0125	.0125
20	.4483	.0996	.0999	.0986	.0126	.0126	.0127	.0126	.0126
30	.4474	.0993	.0998	.0977	.0126	.0127	.0127	.0126	.0126
40	.4466	.0991	.0997	.0970	.0126	.0127	.0128	.0127	.0127
50	.4457	.0989	.0997	.0962	.0127	.0128	.0129	.0127	.0127
60	.4449	.0987	.0996	.0954	.0127	.0128	.0130	.0127	.0127
70	.4446	.0985	.0995	.0947	.0127	.0129	.0131	.0128	.0128
80	.4431	.0983	.0995	.0939	.0128	.0129	.0131	.0128	.0128
90	.4423	.0980	.0994	.0931	.0128	.0130	.0132	.0128	.0128
100	.4414	.0978	.0993	.0924	.0129	.0130	.0133	.0129	.0129

Table 5: *Change in State Probabilities With Time In Useful-Life Phase*

T	P_9	P_{10}	P_{11}	P_{12}	P_{13}	P_{14}	P_{15}	P_{16}	P_{17}
10	.0126	.0129	.0127	.0127	.0126	.0126	.0125	.0125	.0125
20	.0126	.0133	.0130	.0130	.0126	.0127	.0126	.0126	.0125
30	.0127	.0138	.0132	.0132	.0127	.0127	.0126	.0126	.0125
40	.0127	.0142	.0134	.0134	.0127	.0128	.0127	.0127	.0125
50	.0128	.0146	.0137	.0137	.0128	.0129	.0127	.0127	.0125
60	.0128	.0150	.0139	.0139	.0128	.0130	.0127	.0127	.0125
70	.0129	.0155	.0141	.0141	.0129	.0131	.0128	.0128	.0125
80	.0129	.0159	.0144	.0144	.0129	.0131	.0128	.0128	.0126
90	.0130	.0163	.0146	.0146	.0130	.0132	.0128	.0128	.0126
100	.0130	.0167	.0148	.0148	.0130b	.0133	.0129	.0129	.0126

Table 6: *Change in State Probabilities With Time In Useful-Life Phase*

T	P_{18}	P_{19}	P_{20}	P_{21}	P_{22}	P_{23}
10	.0125	.0126	.0126	.0125	.0125	.0125
20	.0126	.0126	.0127	.0126	.0126	.0125
30	.0126	.0127	.0127	.0126	.0126	.0125
40	.0126	.0127	.0128	.0127	.0127	.0125
50	.0127	.0128	.0129	.0127	.0127	.0125
60	.0127	.0128	.0130	.0127	.0127	.0125
70	.0127	.0129	.0131	.0128	.0128	.0125
80	.0128	.0129	.0131	.0128	.0128	.0126
90	.0128	.0130	.0132	.0128	.0128	.0126
100	.0129	.0130	.0133	.0129	.0129	.0126

Table 7: *Change in State Probabilities With Time In Wear-Out Phase*

T	P_0	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8
10	.4492	.0998	.0100	.0993	.0125	.0126	.0126	.0125	.0125
20	.4462	.0994	.0992	.0981	.0125	.0127	.0128	.0127	.0127
30	.4404	.0984	.0980	.0964	.0125	.0131	.0133	.0129	.0129
40	.4321	.0970	.0962	.0942	.0125	.0135	.0139	.0133	.0132
50	.4212	.0952	.0940	.0915	.0125	.0142	.0147	.0138	.0136
60	.4078	.0930	.0912	.0883	.0125	.0149	.0157	.0143	.0141
70	.3918	.0904	.0879	.0846	.0126	.0158	.0169	.0150	.0147
80	.3733	.0873	.0841	.0803	.0127	.0168	.0183	.0158	.0155
90	.3522	.0838	.0798	.0756	.0128	.0180	.0199	.0167	.0163
100	.3285	.0799	.0749	.0703	.0129	.0193	.0216	.0178	.0172

Table 8: *Change in State Probabilities With Time In Wear-Out Phase*

T	P_9	P_{10}	P_{11}	P_{12}	P_{13}	P_{14}	P_{15}	P_{16}	P_{17}
10	.0126	.0129	.0127	.0127	.0126	.0126	.0125	.0125	.0125
20	.0127	.0141	.0134	.0133	.0127	.0128	.0127	.0127	.0124
30	.0131	.0162	.0146	.0144	.0131	.0133	.0129	.0129	.0124
40	.0135	.0191	.0163	.0159	.0135	.0139	.0133	.0132	.0124
50	.0142	.0229	.0185	.0178	.0142	.0147	.0138	.0136	.0124
60	.0149	.0274	.0212	.0202	.0149	.0157	.0143	.0141	.0123
70	.0158	.0328	.0243	.0230	.0158	.0169	.0150	.0147	.0123
80	.0168	.0391	.0280	.0263	.0168	.0183	.0158	.0155	.0123
90	.0180	.0462	.0321	.0300	.0180	.0199	.0167	.0163	.0123
100	.0193	.0541	.0367	.0341	.0193	.0216	.0178	.0172	.0123

Table 9: *Change in State Probabilities With Time In Wear-Out Phase*

T	P_{18}	P_{19}	P_{20}	P_{21}	P_{22}	P_{23}
10	.0125	.0126	.0126	.0126	.0125	.0125
20	.0125	.0127	.0128	.0127	.0127	.0124
30	.0125	.0131	.0133	.0129	.0129	.0124
40	.0125	.0135	.0139	.0133	.0132	.0124
50	.0125	.0142	.0147	.0138	.0136	.0124
60	.0125	.0149	.0157	.0143	.0141	.0123
70	.0126	.0158	.0169	.0150	.0147	.0123
80	.0127	.0168	.0183	.0158	.0155	.0123
90	.0128	.0180	.0199	.0167	.0163	.0123
100	.0129	.0193	.0216	.0178	.0172	.0123

Tables 4 to 9 analysis show that variations in the wear-out phase decrease by 4.5% to 3.2%, while variations in the useful life phase decrease by 4.5% to 4.4% in the good state probability. The variation in the good state probability occurred because of an increase in the failure rate with respect to time during the wear-out phase. The similarity of state probability fluctuates Because of the two facts: (1) The values of their individual weights dominate this summation, making the cumulative effect of the other weights and states insignificant, and (2) The state probability values at time t=0 are presumptively similar, P_4 versus P_{18} and P_{17} versus P_{23} are in both the useful-life and wear-out phases.

Here, the upstate (availability) of the system is indicated in the current ANN model output layer. With the aid of equation (29), the system's time-related availability is computed, and the results are displayed in Table (10) and Figure (3).

Table 10: *Availability of the system*

Time	Availability (Wear-out)	Availability (useful-life)
10	0.7488	0.7481
20	0.7428	0.7462
30	0.7332	0.7443
40	0.7196	0.7424
50	0.7020	0.7405
60	0.6803	0.7386
70	0.6547	0.7367
80	0.6250	0.7348
90	0.5913	0.7329
100	0.5536	0.7310

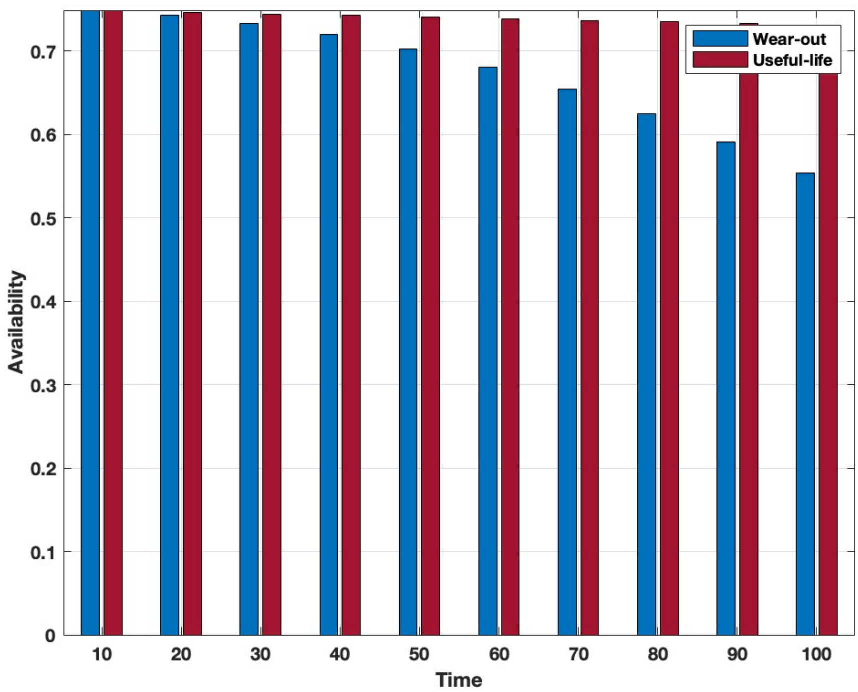

Figure 3: *Availability with Time*

Table 10 analysis shows that the system's availability decreases over time in both the wear-out and useful life phases. The system availability drops from 7.4% to 5.5% during the wear-out phase. On the other hand, availability slightly decreases from 7.4% to 7.3% during the useful-life phase. When compared to the useful-life phase, the availability decrement varies more during the wear-out phase. This variation is caused by the wear-out phase failure rate increasing over time, whereas it remains constant during the useful-life phase.
With the aid of revenue costs and preventive maintenance costs, which fix revenue costs and variable preventive costs, the profit of the continuous casting system is computed using the given

equation.

$$Profit = R_e A(t) - C_1 - C_2 \tag{31}$$

Where R_e, C_1 and C_2 is the revenue cost per unit time, the total cost per unit, and the preventive maintenance cost of time, here we take C_1 =2400, R_e=19000, C_2=56

Table 11: *Profit of the System*

Time	Profit (Wear-out)	Profit (useful-life)
10	11761	11758
20	23371	23499
30	34537	35168
40	45033	46765
50	54632	58290
60	63100	69742
70	70215	81121
80	75745	92429
90	79461	10366
100	81126	11483

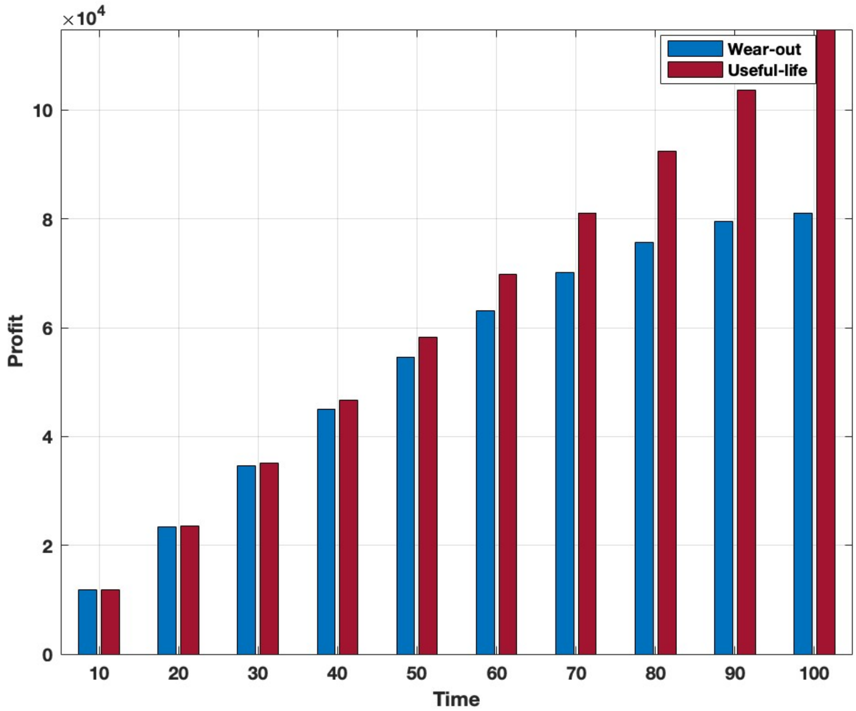

Figure 4: *Profit with Time*

Based on the data presented in Table 11, it can be inferred that the steel industry's casting system's profit increases over time as it wears out and the useful-life phase. The system's wear-out phase turns out to be more profitable than its useful-life phase for the main reason that the wear-out phase's availability exceeds the useful-life phases. Wear-out phase is a strategic focal point for optimizing financial returns because of its direct correlation with increased profitability due to its increased availability.

4. Conclusion

The implementation of Artificial Neural Network (ANN) techniques in the metals industry's continuous casting system has been shown to be beneficial in terms of enhancing productivity parameters. This study uses an artificial neural network (ANN) approach to optimize casting system availability in the steel industry during both the useful life and wear-out phases. Consequently, an ANN model has been used to compare the changes in multi-state probabilities with respect to time for the system's (i) wear-out phase and (ii) useful life phase. Therefore, it can be concluded that while the probability of the good state P_0 decreases dramatically from 44.92% to 32.85% during the wear-out phase, it decreases smoothly from 44.91% to 44.14% during the useful-life segment.

The probability behavior of the degraded states (P_1, P_2, and P_3) is also analyzed. It is found that the wear-out phase has a greater impact on the variation in the degraded state's state probability than the useful-life phase. In the wear-out phase, the probability of degraded states decreases by approximately 9.98% to 7%, whereas in the useful-life phase, it decreases by approximately 9.98% to 9.24%. In both the useful-life and wear-out phases, the state probability of the failed state increases with time.

The availability of the casting system is examined in both the useful life and wear-out phases. It is found that, in comparison to the useful-life phase, the wear-out phase majorly impacts the system's availability. The system's availability drops from 74.9% to 55.4% during the wear-out phase and from 74.8% to 73.1% during the useful life.

The profit margin of the system has also been examined using revenue and preventive maintenance costs, which adjust for revenue and other expenses. It is concluded that, in comparison to a useful-life case, the system yields higher profit in terms of time during the wear-out phase.

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