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ORIGINAL STUDY

Predictive Reliability Assessment and Profit Optimization of an Ice Cream Plant Using an Artificial Neural Network Technique

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ABSTRACT

This study presents a reliability analysis of an ice cream manufacturing facility based on operational failure data. The research develops a ten-component system model that captures plant dynamics and organizes it into three subsystems to reduce computational complexity. The study derives key reliability parameters and constructs a state transition diagram to represent system behavior across multiple operating states. The analysis applies an Artificial Neural Network (ANN) to address the limitations of conventional analytical methods in modeling complex nonlinear systems. The ANN provides strong predictive performance and manages uncertainty within the operational environment. The proposed framework estimates system reliability with high precision and supports maintenance planning and cost optimization. Numerical simulations validate the effectiveness of the ANN-based model. The results demonstrate improved prediction accuracy and greater computational efficiency compared to traditional approaches. State probability deviations are evaluated over a 24-hour period. The up-state probability increases from 95% to 96.02% during the useful life period and from 95% to 96.03% during the wear-out period. The findings confirm that the proposed method enhances reliability prediction, improves maintenance scheduling, and supports cost control and equipment design optimization in ice cream production systems.

Keywords: Artificial neural network, Ice cream plant, Mean time to failure (M.T.T.F), Reliability, State transition

Introduction

The world ice cream market is at a stage of impressive development, with the Asia-Pacific region becoming the major contributor to the ice cream growth. India is the leading dairy producer globally and a market that is undergoing booming growth. This positive trend is essentially driven by the growing demand for frozen desserts in the world, which has been supported by good demographics and the growing economic forces. Nevertheless, this bright future does not go without problems. Systemic shocks are susceptible to the industry due to its seasonality and cold chain dependence. This weakness was clearly seen during the COVID-19 pandemic, which had already caused estimated losses of INR 60 billion to the Indian ice cream industry alone since March 2020, which is normally the time of year when sales peak. In addition to the external shocks, the intrinsic technicity of ice cream as a sophisticated aggregate food product is causing continuous operational challenges. Its production, storage, and distribution involve strict control of temperature and highly advanced procedures, which make it vulnerable to breakdown at various stages. One of the major obstacles to steady growth and profitability is the issue of weak supply chain management. To pass

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these obstacles and utilize the potential of the market, the manufacturers need to attain unparalleled rates of operational efficiency and system reliability. It requires a shift to a more systematic, data-driven approach to the consideration and optimization of all aspects of the production process. A solid analytical system is necessary in order to organize and enhance complicated production processes. The root methodology to this problem is Reliability, Availability, and Maintainability (RAM) analysis. A RAM analysis provides a structured framework for evaluating system performance by focusing on three fundamental characteristics: the ability of the system to operate without failure (Reliability), the ability of the system to perform when required (Availability), and the ease with which the system can be restored to operational condition after a failure (Maintainability).[1] A detailed RAM analysis of an ice cream production line identified the critical components and subsystems whose failures most significantly affect overall system performance. Using failure data carefully to analyze it, such studies outline particular areas to be improved specifically, which shows how, with a systematic RAM approach, direct uptime and productivity will be achieved, which is a vital benefit in a field where time spent in production stops can cost the organization both money and resources. As a monument established on the concepts of RAM, Overall Equipment Effectiveness (OEE) provides a more comprehensive measure of manufacturing productivity. OEE combines the three essential aspects into a single, all-inclusive score.

- **Availability:** Covers the comparison of actual time to the planned time of production.
- **Performance:** This is the speed of actual production compared to the ideal or designed speed.
- **Quality:** It is the number of good units divided by the number of units manufactured.

In a study,[2] the OEE of an automated ice cream production line was studied, which emphasized the need to get a multifaceted perspective in a case study. It has been shown that the availability of machines alone will not bring perfect output; other factors, such as low operating speeds and slight defects in quality, will have catastrophic effects on the total OEE score. This highlights the need to have a holistic approach that goes beyond the simple uptime calculations to include the entire aspect of production efficiency. Engineers have used powerful logical methods to model the complex interactions of the elements in such systems. An example is the Boolean Function Technique (BFT) that offers a means of describing the reliability of a system in terms of a sequence of logical states to enable the determination of both the critical failure points and their propagating effect. The research did a good job in applying BFT to examine a juice packaging plant and provided a quantitative method of assessing reliability. This approach has also been developed through the integration with modern computing tools. Although[3,4] synergistically coupled BFT with neural networking to simulate a chocolate production facility, it can be shown that integrating classical logic with machine learning can be a more dynamic and predictive framework for maintenance and operations management. Industry 4.0 and Quality 4.0 concepts are implemented in the field of sustainable development and supply chain resilience to activities on the microenterprise level, on the one hand, and the FMCG industry, on the other hand,[5,6] It can be done through the use of frameworks such as Quality Function Deployment (QFD) to combine real-time data and predictive analytics to avoid defects even before they arise,[7] explores. This change depends upon the facilitating technologies of Digital Twins, AI, and distributed ledgers that are coming together to improve complex systems like food logistics.[8–11] The performance forecasting of renewable energy and intelligent fault diagnosis of food production rely on machine learning, which leads to traditional reliability and cost-analysis methods to optimize system availability and performance.[12,13] At the core of revolution is Artificial Neural Networks, or ANNs, that have become a formidable weapon of predictive reliability measures. The beauty of ANNs is that they can capture the non-linear, complex relationships that are present in the modern industrial system, and therefore they are the most suitable in predicting equipment reliability and avoiding the expensive downtime.[14,15] The flexibility of the models is proven by their effective usage in a wide range of areas, including software reliability and communication networks, which proves the appropriateness of the models in the highly integrated machinery of a food production facility.[16–18] In the food industry in particular, the potential of AI is already being fulfilled on the value chain. It is being applied to critical risk assessment along the supply chain,[19] which is a crucial feature to manage the perishable nature of the ice cream ingredients. Specialized architectures such as convolutional neural networks are automating quality control inspection and detecting patterns of data indicating deviation in processes in quality control.[20,21] Additionally, AI is also finding application in product integrity as well as fighting food fraud since large datasets can be analyzed using AI to predict possible contamination,[22,23] which can directly be used to authenticate the quality of dairy ingredients.[24] Lastly, AI is also being utilized to optimize the food processing itself so that it can be operated in a more sustainable and efficient way by way of optimized energy use and reduced waste, which goes directly back into profitability.[25,26] This extensive technological implementation, which also encompasses augmented reality in training and maintenance of workers,[27] is an indication of an all-encompassing change in contemporary food production. The integration of traditional reliability engineering and current intelligent systems creates a new horizon in streamlining the performance of manufacturing. The growing complexity of systems that can nowadays be studied requires a strict emphasis on the issue of reliability, not just as a technical task but as a strategic measure to guarantee the predictability of the operations and profitability.[28–30] The study exists in the overlap of these vital areas, with an organized analytical methodology for a complicated food processing system. The ways of evaluating the reliability of the systems and their evaluation have developed with time, with an increasing number of more advanced tools of analysis and calculations. The basic research, including,[31] demonstrated how the Boolean Function (BF) method could be used to determine the reliability and Mean Time To Failure (MTTF) of subsystems such as power plants. This indicates that a long-running attempt has been made to mathematically model system failure. Later on, these classical methods have been combined with contemporary computational intelligence. An illustration of this is,[32] which implemented a hybrid methodology by using both a Boolean algebra and neural networks to determine reliability aspects on a glass manufacturing facility. Reliability in system design is further discussed by,[33] who employed the stochastic analysis to simulate computer systems with cold standby redundancy to show how architectural decisions are vital in enhancing fault tolerance. First in this development,[34,35] applied probabilistic machine learning to structural reliability analysis, a change in direction to predictive models capable of better dealing with uncertainty than deterministic methods. In addition to pure reliability modeling, the overall inclusion of the cutting-edge technologies is transforming the industrial practice, both in the manufacturing sector and the food industry[36] give a general picture of how the technologies of the Fourth Industrial Revolution can be utilized in the dairy industry. This is also being traced in terms of particular technological use in the food sector. Likewise,[37] investigated the position of the non-thermal processing of probiotic foods, a change in technology to enhance the quality and safety of the product, which is one of the major dimensions of the overall system functioning. Thus, the key aims of the paper will be to illustrate the complex structure and operation systems of a modern ice cream factory and to perform a detailed analysis

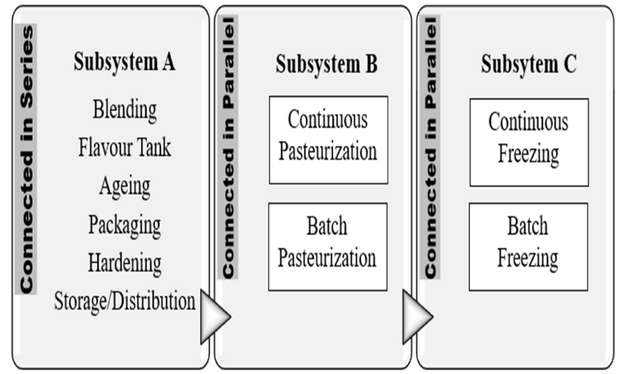

Fig. 1. Block diagram of the Series-parallel Ice-cream plant system.

of the viability of this factory. In this respect, the required assumptions will be formulated at the beginning, and the important system parameters will be determined. The results of our reliability analysis will then be provided in the paper, with a cost evaluation of the operations of the plant. Lastly, the paper offers a conclusion that is a summary of the findings and suggests how future research can be done in this important sector of the industry.

Systematic configuration

It is an ice cream plant that uses 10 ingredients in three different stages. The first step (components 1–3) involves the unpasteurized ingredient blending. The pasteurized mixture is processed in the second stage (components 4–5). Lastly, the third phase (components 6–10) entails ice cream freezing. The block diagram in Fig. 1 depicts the successful function of the production line. The Ice- Cream plant under consideration is divided into three subsystems: A, B, and C.

Subsystem A is a series system consisting of six critical components: Blending, Ageing, Flavour Tank, Packaging, Hardening, and Storage/Distribution. Due to the serial configuration, a failure in any of these components will halt the entire production line unless promptly repaired. No standby units are available.

Subsystem B (Pasteurization): It consists of two components of the production lines under consideration, i.e., Continuous Pasteurization (B1) and Batch Pasteurization (B2). This research has contemplated that this subsystem will never fail. If one component of this subsystem fails, then the other will act as a stand-by for that component.

Subsystem C (Freezing): It consists of two components of the production lines under consideration, i.e., Continuous Freezing (C1) and Batch Freezing (C2). This research has contemplated that this subsystem will never fail. If one component of this subsys-

Table 1. Steady-state probabilities, failure and repair rates.

Steady State Probabilities	Failure Rates	Repair Rates
P0: The whole system is in a completely workable state.	f1: Subsystem A	r_1 : Subsystem A
P1: Subsystem A fails, and the whole production system fails.	f2: Subsystem B1	r_2 : Subsystem B1
P2: Subsystem B1 fails, and the production system works with degraded efficacy.	f3: Subsystem B2	r_3 : Subsystem B2
P3: Subsystem B2 fails, and the production system works with degraded efficacy.	f_4 : Subsystem C1	r_4 : Subsystem C1
P4: Subsystem C1 fails, and the production system works with degraded efficacy. P5: Subsystem C2 fails, and the production system works with degraded efficacy.	f_5 : Subsystem C2	r_5 : Subsystem C2

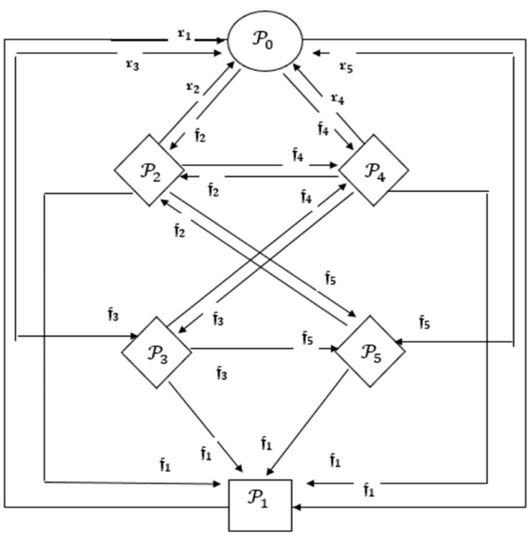

Fig. 2. State transition diagram of the Ice-cream plant.

tem fails, then the other will act as a stand-by for that component. Table 1 provides the steady-state probabilities, failure rates, and repair rates for this production system. Fig. 2 illustrates the state transition diagram of the Ice-Cream Plant, depicting the different operating states of the system and the possible transitions between them.

Fig. 2 illustrates the state transition model of the Ice-Cream Plant, depicting the operational states P0–P5. The directed arrows represent the possible transitions among these states, determined by the associated failure and repair rates. Table 1 presents the various failure and repair rates associated with the system.

Assumptions

The following assumptions for the model are taken into account before initializing the computations.

1) The system is functional at the initial stage.
2) A repair facility is available for a failed component at a constant rate.
3) A repaired component works like a new component with full capacity.
4) For each component, reliability is anticipated.
5) For each component, the state is statistically independent.
6) Failure time is random for each component.
7) For both subsystems B and C, one of the two components is always in a workable state.

Model formulation

ANNs are made to resemble the operation of the human brain. The input information is given in an ANN model, which is accompanied by relevant target valid information, and the process of learning occurs in several iterations (called epochs) with the aim of the model reducing the error. The fundamental principle of an ANN is based on the biological neurons in the brain, since each of the artificial neurons performs the roles of a processing unit. These neurons are the receivers of signals that are classified as input signals, weights are applied, and the output signals are produced by them.

The reliability modeling of the system was done with the ANN technique in this study. With this method, the change in the probabilities of each state of the system was estimated in minute time intervals (Δt). This is an iterative process, which enabled the ANN model to forecast the variations in state probabilities with the passage of time, an operation that offered a dynamic level of reliability of the system.

The proposed model has a feed-forward network with multiple layers. These layers include an input layer, an output layer, and a hidden layer. The neurons are located in these layers.

Input Layer: There are six neurons in this layer associated with the six steady-state probabilities fed as input data. Thus,

$$\mathcal{X}_k = \mathcal{P}_k(t), \text{ where } 0 \le k \le 5$$

Neural Weights: The weights are assigned according to the failures and repairs of the Components are given as,

$$w_{01} = w_{21} = w_{31} = w_{41} = w_{51} = f_1 \Delta t \quad (1)$$

$$w_{02} = w_{42} = w_{52} = f_2 \Delta t \tag{2}$$

$$w_{03} = w_{43} = w_{53} = f_3 \Delta t \tag{3}$$

$$w_{04} = w_{24} = w_{34} = f_4 \Delta t \tag{4}$$

$$w_{05} = w_{25} = w_{35} = f_5 \Delta t \tag{5}$$

$$w_{10} = r_1 \Delta t \tag{6}$$

$$w_{20} = r_2 \Delta t \tag{7}$$

$$w_{30} = r_3 \Delta t \tag{8}$$

$$w_{40} = r_4 \Delta t \tag{9}$$

$$w_{50} = r_5 \Delta t \tag{10}$$

$$w_{00} = 1 - w_{01} - w_{02} - w_{03} - w_{04} - w_{05} \tag{11}$$

$$w_{11} = 1 - w_{10} \tag{12}$$

$$w_{22} = 1 - w_{21} - w_{24} - w_{25} - w_{20} \tag{13}$$

$$w_{33} = 1 - w_{31} - w_{34} - w_{35} - w_{30} \tag{14}$$

$$w_{44} = 1 - w_{41} - w_{42} - w_{43} - w_{40} \tag{15}$$

$$w_{55} = 1 - w_{51} - w_{52} - w_{53} - w_{50} \tag{16}$$

Activation Function: It is given in the hidden layer as $g(z_m)$, where,

$$z_m = \sum_{k=0}^{5} w_{mk} X_k + b_m, \text{ for } 0 \le m \le 5 \tag{17}$$

The activation function is linear. The summation in the above Eq. (17) represents a weighted sum, and b_m is known as bias.

Output Layer: The output signals are calculated by the activation function or the transfer function given below,

$$Y_k = P_k(t + \Delta t), \text{ where} 0 \le k \le 5. \tag{18}$$

Using ANN in Eq. (18),

$$Y_m = g(z_m) = g\left(\sum_{k=0}^{5} w_{mk} X_k + b_m\right), \; for\ 0 \le m \le 5 \tag{19}$$

Solution of the Model

After solving the ANN model, the output signals are given in Eqs. (20) to (25)

$$Y_0 = w_{00}X_0 + w_{10}X_1 + w_{20}X_2 + w_{30}X_3 + w_{40}X_4 + w_{50}X_5 + b_0 \tag{20}$$

$$Y_1 = w_{01}X_0 + w_{11}X_1 + w_{21}X_2 + w_{31}X_3 + w_{41}X_4 + w_{51}X_5 + b_1 \tag{21}$$

$$Y_2 = w_{02}X_0 + w_{22}X_2 + w_{42}X_4 + w_{52}X_5 + b_2 \tag{22}$$

$$Y_3 = w_{03}X_0 + w_{33}X_3 + w_{43}X_4 + w_{53}X_5 + b_3 \tag{23}$$

$$Y_4 = w_{04}X_0 + w_{44}X_4 + w_{24}X_2 + w_{34}X_3 + b_4 \tag{24}$$

$$Y_5 = w_{05}X_0 + w_{55}X_5 + w_{25}X_2 + w_{35}X_3 + b_5 \tag{25}$$

Thus, the upstate and downstate probabilities P_{up} *and* P_{down}, respectively, are given below as Eqs. (26) and (27).

$$P_{up} = Y_0 + Y_2 + Y_3 + Y_4 + Y_5 \tag{26}$$

$$P_{down} = Y_1 \tag{27}$$

$$P_{up} + P_{down} = 1 \tag{28}$$

Results and discussion

For the proposed ANN model, time has been considered as a factor to compare the state probabilities and to perform numerical computations. The system is assumed to operate continuously. The time factor t has been taken for evaluation in months. The initial time is considered $t_0 = 24$ hours $= 0.03$ months and $\Delta t = 24$ hours $= 0.03$ months. In this proposed model, considering bias $b_m = 0\ \forall m$. The neural weights are associated with failure and repair rates given in Eq. (1) to Eq. (25) and are evaluated as a combination of both. The output values given by Eqs. (20) to (25) is the summation of the weights to the input values. The input signal values are given as initial state probabilities in Table 2 below,

Table 2. Initial state probabilities.

Initial State Probabilities $P_k = X_k$					
P_0	P_1	P_2	P_3	P_4	P_5
0.55	0.05	0.1	0.1	0.1	0.1

Table 3. The failure rate for each component of the Ice-cream plant.

Repair Rate (χ_i)		Failure Rate (f_i)	Constant	Shape Parameter (β)	Scale Parameter (η)	Weibull (At time t_0)
χ_1	0.8479	f_1	0.004	2	3.942	0.003861162
χ_2	0.0367	f_2	0.0007	2	9.205	0.000708115
χ_3	0.0367	f_3	0.0007	2	9.205	0.000708115
χ_4	0.0407	f_4	0.0005	2	10.896	0.000505379
χ_5	0.0407	f_5	0.0005	2	10.896	0.000505379

The repair rate and failure rate of the system states are given in Table 3. The repair rate remains constant with time, whereas for the failure rate, two cases are considered.

- Case 1, where the failure rates are constant with time, which depicts the useful life of the system. In this case, failure rates are assumed to follow the Exponential Distribution.
- Case 2, where the failure rates depend upon time, which depicts the wear-out phase of the system. In this case, failure rates are assumed to follow the Weibull Distribution with time as a factor. The failure rate $\mathfrak{f}(t)$ is thus given as $\mathfrak{f}(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1}$ where β is the shape parameter and η is the scale parameter.

The deviations in state probabilities are measured for different values of time with an increment of 24 hours. The output signal values for the constant failure rate (when failure rate follows the Exponential Distribution), i.e., the useful lifetime is measured using the Eqs. (20) to (25). The calculated values are in Table 4 and Fig. 3. It can be observed from the table that the probability of the states working with degraded efficiency, i.e., $\mathcal{P}_2,\ \mathcal{P}_3,\ \mathcal{P}_4,$ *and* $\mathcal{P}_5$ is decreasing, and the difference is less.

The deviations in state probabilities are measured for different values of time with an increment of 24 hours. The output signal values for the failure rate (when failure rate follows Weibull Distribution), i.e., the wear-out phase are measured using the Eqs. (20) to (25). The calculated values are given in Table 5 and Fig. 4.

Table 6 shows the difference in upstate and downstate probabilities given in Eqs. (26) and (27). For the useful life period, the increase in upstate probability is from 95% to 96.02%, and for the wear-out phase,

Table 4. State probabilities with time (Useful life).

Time (t) (hrs.)	$\mathcal{P}_0$	$\mathcal{P}_1$	$\mathcal{P}_2$	$\mathcal{P}_3$	$\mathcal{P}_4$	$\mathcal{P}_5$
0	0.55	0.05	0.1	0.1	0.1	0.1
24	0.551631	0.048842	0.099891	0.099891	0.099873	0.099873
48	0.553624	0.047427	0.099757	0.099757	0.099718	0.099718
72	0.555436	0.046141	0.099636	0.099636	0.099577	0.099577
96	0.557247	0.044854	0.099514	0.099514	0.099435	0.099435
120	0.559059	0.043568	0.099393	0.099393	0.099294	0.099294
144	0.560871	0.042281	0.099279	0.099271	0.099153	0.099153
168	0.562683	0.040995	0.09915	0.09915	0.099012	0.099012
192	0.564495	0.039708	0.099028	0.099028	0.098871	0.098871

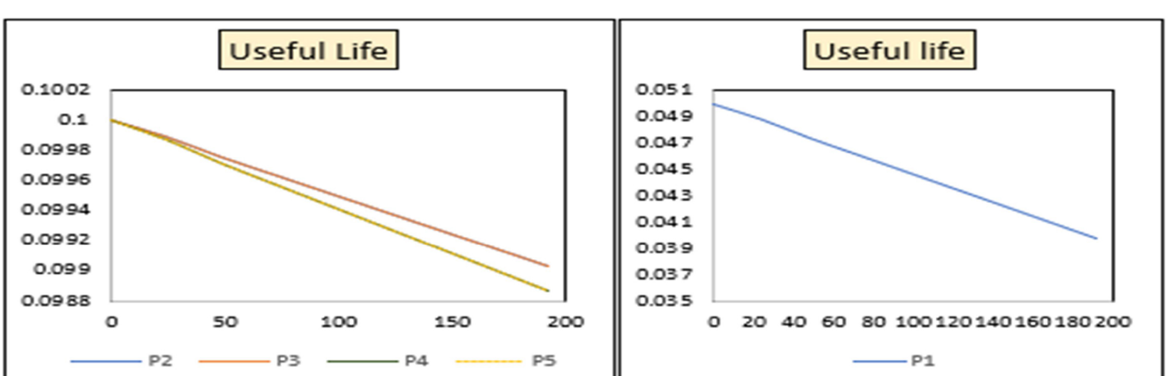

Fig. 3. Useful life probabilities.

Table 5. State probabilities time (Wear out phase).

Time (t) (hours)	$\mathcal{P}_0$	$\mathcal{P}_1$	$\mathcal{P}_2$	$\mathcal{P}_3$	$\mathcal{P}_4$	$\mathcal{P}_5$
0	0.55	0.05	0.1	0.1	0.1	0.1
24	0.551813	0.048711	0.099879	0.099879	0.099859	0.099859
48	0.553628	0.047418	0.099758	0.099758	0.099719	0.099719
72	0.555442	0.046127	0.099637	0.099637	0.099578	0.099578
96	0.557256	0.044836	0.099517	0.099517	0.099438	0.099438
120	0.559069	0.043546	0.099396	0.099396	0.099297	0.099297
144	0.560883	0.042255	0.099275	0.099275	0.099156	0.099156
168	0.562697	0.040964	0.099154	0.099154	0.099016	0.099016
192	0.564511	0.039673	0.099033	0.099033	0.098875	0.098875

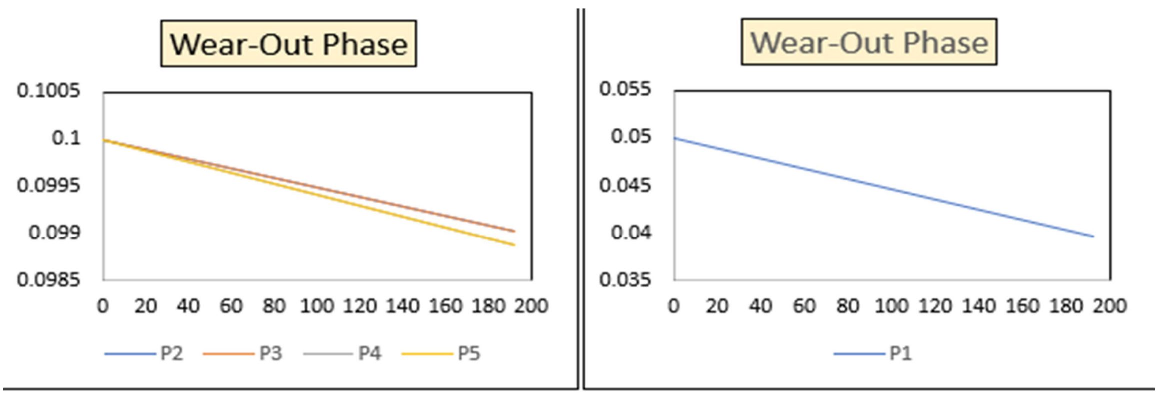

Fig. 4. Wear-out phase probabilities.

the increase is from 95% to 96.03%. It is clear from the table that $\mathcal{P}_{up} + \mathcal{P}_{down} = 1$

As shown in Fig. 5, the system exhibits strong predictive consistency across both models, confirming the plant's high reliability and robust performance.

Fig. 5 shows that over a 192-hour period, the system shows stable behavior, with a slight increase in operational probability $\mathcal{P}_{up}$ and a slight decrease in downtime probability $\mathcal{P}_{down}$. $\mathcal{P}_{up}$ Consistently stays above 0.95, indicating high system reliability, while $\mathcal{P}_{down}$ remains below 0.05, reflecting minimal downtime. Both constant and time-dependent failure models yield nearly identical results, suggesting time dependency has a negligible impact under the given parameters.

Cost analysis

Optimization of cost is the most important goal in assessing the reliability of an industrial plant to maximize profits and minimize losses. It is important to consider the maintenance cost while maximizing the cost for upstate probabilities for more than 90%. Many costs are included in the ice cream plant under consideration, other than the maintenance cost. These costs come under service costs and include labour, raw materials, . . ., etc.

Thus, the expected cost or the profit function [33] is given by $S(t) = S_1 A_0(t) - (S_2 + S_3)t$

Where S_1 is the revenue cost per unit time, S_2 is the service cost per unit time, and S_3 is the maintenance

Table 6. Upstate and downstate probabilities.

	Constant Failure		Time-dependent Failure	
Time (t)(hours)	$\mathcal{P}_{up}$	$\mathcal{P}_{down}$	$\mathcal{P}_{up}$	$\mathcal{P}_{down}$
0	0.95	0.05	0.95	0.05
24	0.951158	0.048842	0.951291	0.048709
48	0.952573	0.047427	0.952582	0.047418
72	0.95386	0.046141	0.953873	0.046127
96	0.955146	0.044854	0.955164	0.044836
120	0.956433	0.043568	0.956454	0.043546
144	0.957719	0.042281	0.957745	0.042255
168	0.959006	0.040995	0.959036	0.040964
192	0.960292	0.039708	0.960327	0.039673

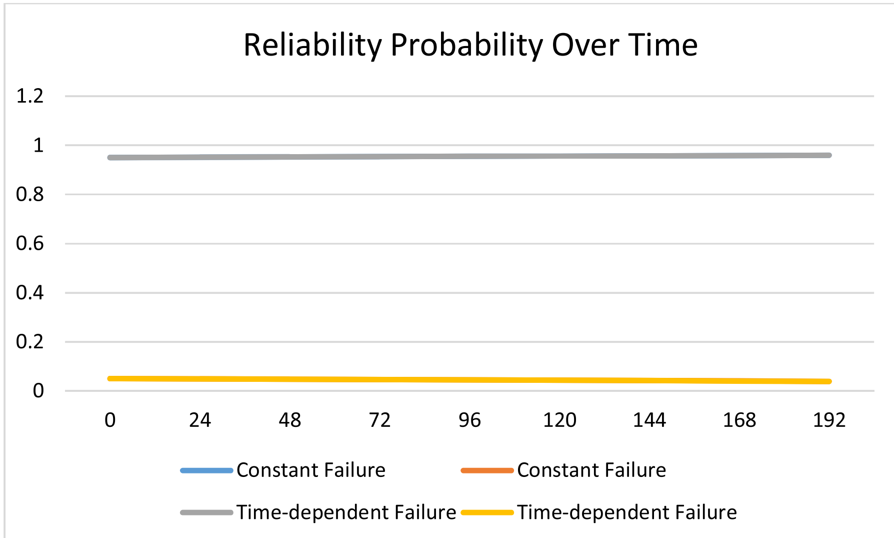

Fig. 5. Reliability probability over time.

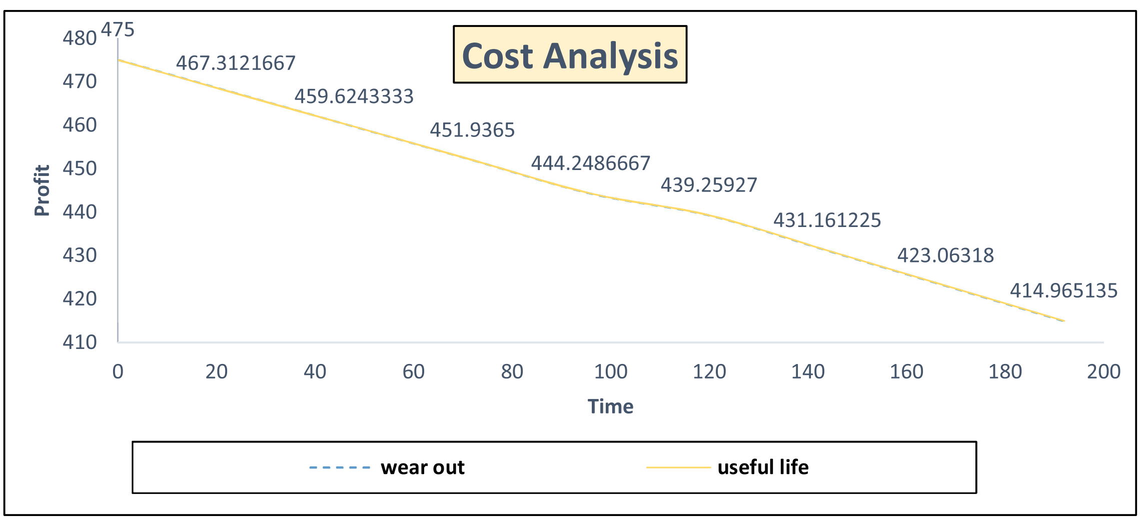

Fig. 6. Cost analysis for useful life period and wear-out phase period and wear-out phase.

cost per unit time. $A_0(t)$ is the availability of the system.

In this case, two cases are considered to calculate the expected cost for the upstate probabilities. The two cases are for the useful life period and the wear-out phase. The upstate probabilities for both cases are given in Table 6. All time values are given in hours, adjusted by 24-hour increments. The revenue cost per unit time is taken as $S_1 = \$500$ Initially, and after 120 hours, it is increased by 1%. The combined service and maintenance cost is initially taken as $S2=\$250$, and after 120 hours, it increases by 5%. Since the difference is less in the upstate probabilities for both cases, the useful period and the wear-out phase, the difference in expected cost is also less, as shown in Fig. 6.

The graph in Fig. 6, clearly shows a consistent decline in profit over time. The "useful life" line starts at a value of 473 and drops to around 415 by time 200, a clear indicator of asset depreciation. The cause of this downward trend is the higher operating costs and low efficiency owing to normal wear and tear. This loss is especially significant in such sectors as food processing, where the equipment can become worn out within a short period of time. In an ice cream production facility, such as one, equipment is very prone to quick depreciation, and any form of stalling translates to a huge loss. Owing to this reason,

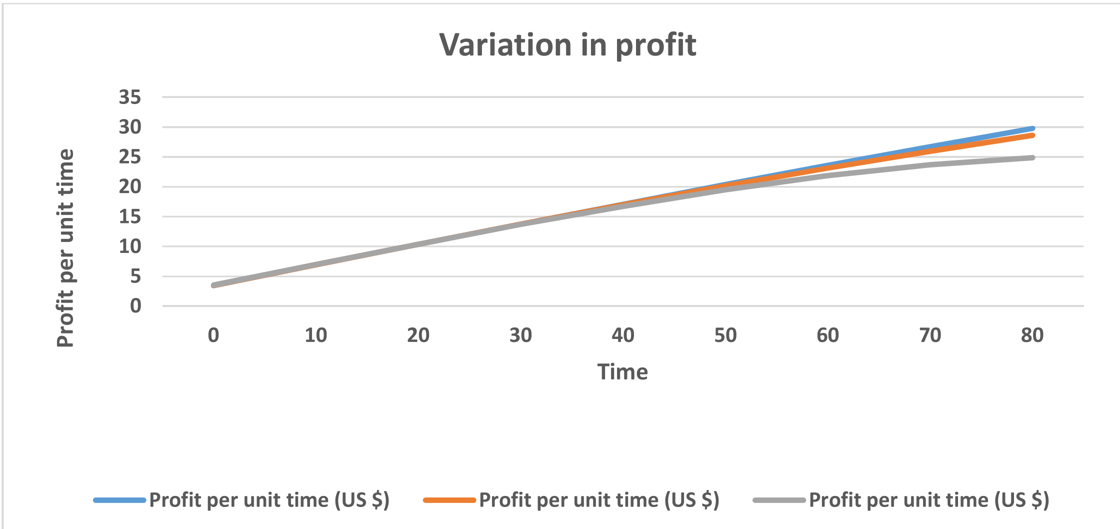

Fig. 7. Variation in profit with respect to maintenance.

preventive maintenance (PM) is a requirement. It is important to know this rate of decline. Through predictive reliability tests and proactive maintenance, companies can intervene early enough to increase the useful life span of an asset and also maximize its performance which is lost quickly once it has not undergone the necessary maintenance. Fig. 7 shows the change in terms of profit per unit time with and without preventive maintenance.

As observed in Fig. 7, systems that use the preventive maintenance (PM) strategy regardless of whether it is using a maximum or minimum number of repairs and replacements all result in high profitability relative to those that do not implement the preventive maintenance strategy. This is because PM reduces the cost of unplanned downtime and the cost of failure which is extremely beneficial in the profitability of the entire system in the long run. Even though the two PM methods are effective, the higher rate of repairs and replacements in the more aggressive maintenance schedule will lead to slightly better performance of the assets and profit margins. This demonstrates that a maximum repair maintenance strategy can be more profitable, although the initial cost is higher. Conversely, a lack of a PM strategy means a loss of profit in a slow manner. The reason is that it has been marked by the escalation of failure rates, more unplanned down times, and operational inefficiencies. Predictive maintenance propelled by AI, including ANN, is a situation where the organization anticipates and solves small issues before they escalate into large-scale breakdowns. This guarantees a continuous production process and removes the massive losses in revenue that are connected to unexpected downtime. In the end, this method not only reduces maintenance costs but also prolongs equipment longevity, which automatically has a positive effect on profit margins.

Conclusion

In this paper, a profit analysis was conducted for an ice cream factory in order to determine its reliability. Employing an Artificial Neural Network (ANN), the multi-state system of the factory, which runs continuously and degrades gradually, was simulated. Since the ANN modelling technique is not bound by the requirement of assuming any particular lifetime distribution of the system, it can be easily used in predicting variations in state probabilities and profit functions. Given the rapid deterioration of the plant's heavy-duty equipment, our focus was on short-term reliability rather than long-term assessments. Two probability distributions were utilized: the exponential distribution for the useful life period (constant failure rate) and the Weibull distribution for the wear-out phase (time-dependent failure rate). The analysis shows improvement in the system's "upstate" probability. For the useful life period, it increased from 95% to 96.02%, and for the wear-out phase, it saw a similar rise to 96.03%. We have calculated our costs with combined service and maintenance costs, which were growing by 5% at 120 hours, but revenue rose by 1% in the same time. As the components are more prone to wear, as time passes, this will take the system into the wear-out stage, and therefore it is necessary to carry out the maintenance on time to reduce losses.

Authors' declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Furthermore, any Figures and images that are not ours have been included with the necessary permission for re-publication, which is attached to the manuscript.
- No animal studies are present in the manuscript.
- No human studies are present in the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee at Amity University Noida.

Authors' Contribution statement

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by A. T. The first draft of the manuscript was written by S.G., M.K., and A.C., supervised the finding of this work. All authors read and approved the final manuscript.

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تقييم الاعتمادية التنبؤية وتحسين الأرباح لمصنع آيس كريم باستخدام تقنية الشبكات العصبية الاصطناعية

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الخلاصة

تقدّم هذه الدراسة تحليلًا للاعتمادية في منشأة لتصنيع الآيس كريم استنادًا إلى بيانات الأعطال التشغيلية. وقد تم تطوير نموذج يتكوّن من عشرة مكوّنات لتمثيل ديناميكية المصنع، وتنظيمه في ثلاثة أنظمة فرعية لتقليل التعقيد الحسابي. كما اشتملت الدراسة على اشتقاق معلمات الاعتمادية الرئيسة وبناء مخطط انتقال حالات لتمثيل سلوك النظام عبر حالات تشغيل متعددة. تعتمد الدراسة على استخدام الشبكات العصبية الاصطناعية (ANN) لمعالجة القيود المرتبطة بالأساليب التحليلية التقليدية في نمذجة الأنظمة غير الخطية المعقدة. وقد أظهرت الشبكة العصبية أداءً تنبؤيًا قويًا وقدرة على التعامل مع عدم اليقين ضمن البيئة التشغيلية. ويتيح الإطار المقترح تقدير اعتمادية النظام بدقة عالية، ويدعم تخطيط الصيانة وتحسين التكاليف. وقد أثبتت المحاكاة العددية فاعلية النموذج المعتمد على الشبكات العصبية الاصطناعية، حيث أظهرت النتائج تحسنًا في دقة التنبؤ وكفاءة حسابية أعلى مقارنة بالأساليب التقليدية. كما تم تقييم انحرافات احتمالات الحالات على مدى 24 ساعة. وارتفع احتمال حالة التشغيل (Up-State) من 95% إلى 96.02% خلال فترة العمر الإنتاجي، ومن 95% إلى 96.03% خلال فترة التآكل. وتؤكد النتائج أن المنهجية المقترحة تعزز دقة التنبؤ بالاعتمادية، وتحسّن جدولة الصيانة، وتدعم التحكم في التكاليف وتحسين تصميم المعدات في أنظمة إنتاج الآيس كريم.

الكلمات المفتاحية: الشبكات العصبية الاصطناعية، مصنع الآيس كريم، متوسط الزمن حتى الفشل (M.T.T.F)، الاعتمادية، انتقال الحالات.