STOCHASTIC MODELING AND PERFORMABILITY ANALYSIS OF REPAIRABLE SYSTEM OF A PLYWOOD INDUSTRY

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Abstract

The current paper analyzes the performance behavior concerning the performability of the Veneer layup system in a plywood industry. A Markovian Approach is utilized to develop a process model for the system and enhance to evaluate system performability i.e. the function of system availability. The study investigates the impact of varying failure and repair rates on the availability of system, variation in the availability is also determined by varying available repair facilities, using a licensed software package. Particle Swarm Optimization (PSO) method has been employed to optimize the results. Additionally, a Decision Support System (DSS) has been proposed for making strategic decisions regarding financial investments and maintenance order priorities. The findings of the paper will aid the practitioners in deciding the maintenance order priorities among various subsystems.

Keywords:, Performability, Markov Chain, Decision Support System, Particle Swarm Availability Optimization

I. Introduction

The manufacturing process of plywood involves several intricate stages, including veneer cutting, placing up and gluing operations, pressing, and finishing processes. As market competition intensifies, manufacturers must continually enhance the performance of production processes. The utilization of human labor offers flexibility, yet the need for varying sizes of the final product often disrupts the layup stage, a critical phase. This condition has adversely affected factors such as availability, production costs, quality, and in some cases, operator safety. However, modern business communities within these sectors have turned this challenge into a learning opportunity. Industrialists are fervently engaged in operating process plants and industries continuously, aiming to minimize the breakdowns in this competitive era. This endeavor is essential for maintaining maximum productivity and ensuring the highest profits to ensure the survival of the industry concerned.

The performance of a system is enhanced through proper design and maintenance throughout its service life. Through a case study analysis, the paper demonstrates how Markov techniques can provide insights into system performance to identify bottlenecks and suggest strategies for improving production efficiency and product quality. The findings underscore the potential of Markov models as valuable tools for decision-making and process optimization in the plywood industry. Tewari and Khan [11] discussed by using quasi-independence Markov chain and entropy methods, demonstrate a predictable sequence of sedimentary structures, reflecting typical fluvial channel processes. Malik and Tewari [6] dealt with the performance modeling and maintenance order priorities for the Feed Water System in a thermal power plant based on coal and also analyzed the system process by using Chapman-Kolmogorov equations and Markov approaches. Abedi, Yoon, and Kwon [1] discussed a cyclic time-dependent Markov process and reinforcement learning for a battery energy storage control system. Wu and Hoa [12] optimized feature mappings and Markovian models using the Koopman operator's top singular components and introduces score functions for model optimization. Khan and Tewari [3] introduced the Kolmogorov criterion for analyzing transition matrices of reversible Markov processes.

Malik [5] developed a performability model for the Coal Ash Handling System (CAHS) in a thermal power plant operating at subcritical conditions. This model is constructed by aggregating state probabilities using a normalizing condition. Parkash [8] designed Performance Modeling and proposed a DSS to prioritize repairs tasks for an assembly line system. Kumar [4] proposed a Decision Support Priorities (DSP) framework, highlighting the criticality of different useful units. Singh and Tewari [9], Sheikh and Tewari [10] discussed the applications of Reliability, Availability, Maintainability and Safety (RAMS) concepts in various process industries for enhancement of performability. Stochastic processes deal with randomness in systems, like how things change over time in unpredictable ways. Performability analysis facilitates the performance behavior of the system concerned. This helps us make smarter choices about how to design and run systems to make them more reliable and effective.

The Markovian approach analyzes systems based on present states, regardless of past events. It's useful for systems with discrete states and helps prioritize maintenance in assembly lines by modeling subsystem performance. Hale et. al. [2] explored the use of quantitative or conceptual methods to create the Markov chain model of particular industrial unit. Marcozzi and Mostarda [7] discussed stochastic processes for Byzantine Fault Tolerant performance evaluation.

Particle Swarm Optimization (PSO) is a computational optimization method inspired by the collective behavior of birds or fish in search of their food. In PSO, a group of potential solutions, called particles, navigates the search space to locate the optimal solution. Through iterative adjustments, PSO effectively converges towards the optimal solution. A DSS is a high-tech tool that helps decision-makers to analyze the data, generate the reports, and evaluate the alternatives to make the right decisions quickly and effectively.

II. System Description

In the plywood industry, there are typically nine primary steps involved in the production process. These include (a) log collection, (b) debarking, (c) steaming blocks, (d) peeling blocks and veneer cutting machine, (e) drying veneers, (f) gluing and stacking the veneers on top of each other, (g) pressing the veneers in hot and cold presses, (h) trimming the plywood, and (i) super finishing and grade stamping, as illustrated in Figure 1. In plywood industry veneer production system is accounts for approximately 37 to 42% of the total plant output. The system is being studied as plywood industry and base material used as poplar and eucalyptus wood, situated within the Ganga basin of Northern India, this area encompasses several subsystems. These subsystems include:

- **Debarking Machine:** Debarking machine removes bark from logs before to turned into plywood sheets. Logs go in, bark comes off using rotary cutters or water jets, and clean logs come out for further processing. This step ensures high-quality veneer or chips free from bark-related defects and contaminants, extending the life of subsequent machinery.

- **Veneer Cutting Machine:** Veneer cutting machines are vital in woodworking and plywood manufacturing, turning logs into thin, even veneer sheets. Then use rotating blades or drums to slice layers from logs, ensuring consistent thickness and quality. These machines vary in design and features, customized for different wood types and production needs, with some equipped with automation for improved efficiency.
- **Veneer Drier:** A veneer dryer is a specialized subsystem in plywood production, extracting moisture from freshly cut veneer sheets to achieve the desired moisture content for further processing and storage. Through controlled heat and airflow, it prevents defects like warping or cracking. Techniques like hot air circulation or infrared radiation may be used depending on the dryer's design. Efficient moisture removal is vital for producing high-quality plywood sheets with uniform thickness and strength.
- **Gluing and Pasting:** Gluing and pasting are key processes in plywood production. Veneer surfaces are prepared and coated with adhesive before being stacked and pressed to create strong bonds. Curing ensures structural integrity, followed by trimming and finishing for precise dimensions and surface quality. This results in resilient plywood panels used in construction and furniture.

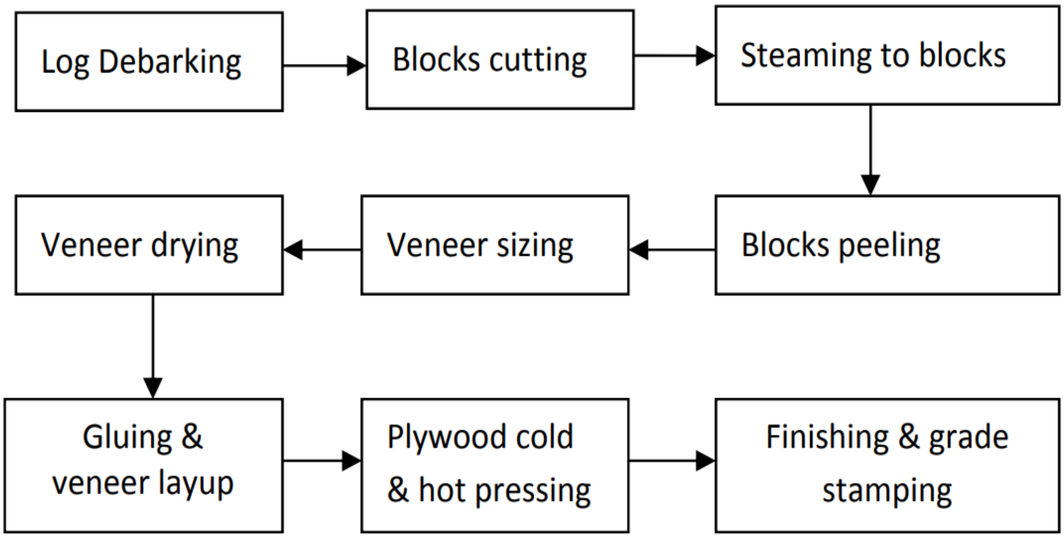


Figure 1: *Flow Diagram of Plywood Manufacturing Process*

The plywood - making process involves preparing veneer sheets from logs, sorting and grading them, sanding or cleaning for adhesion, applying adhesive, stacking with perpendicular grain orientations, pressing to activate the adhesive, curing, and finally trimming and finishing for precise dimensions and quality.

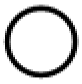
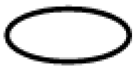
III. Assumptions and Notations

Markov chains rely on several assumptions to effectively model systems. Firstly, to assume stationary, meaning that transition probabilities between states remain consistent over time. This assumption is vital for the stability of the model, allowing us to make reliable predictions about future states based on current probabilities. In other term the probability of transitioning to the next state depends solely on the current state and is unaffected by the history of previous states.

This simplifies the model and makes computations more manageable. The most important assumption is a finite state space, implying that the set of possible states the system can occupy is finite and well-defined. To construct a transition matrix that encapsulates all possible state transitions. Furthermore, assume homogeneity, meaning that transition probabilities are consistent across different time periods. This assumption is essential for making long-term predictions about the system's behavior without being influenced by short-term fluctuations.

Notifications play a vital role in keeping all involved informed about the system's dynamics and relevant updates. Hence to encompass alerts concerning state transitions, providing clear insights into the current state and the probabilities associated with transitioning to subsequent states. Regular updates on state probabilities, derived from observed transitions, enable continuous tracking of the system's behavior over time. The performance modeling of the system relies on certain assumptions and notations, which are as follows:

a) Assumptions:
- Failure and Repair rates are constant over time and statistically independent.
- The system has the potential to operate at a reduced capacity.
- The standby systems exhibit similar characteristics to the active system.
- Service encompasses both repair and replacement of components.
- Simultaneous failures do not take place.
- A subsystem that undergoes repair is considered to be in a condition equivalent to new for a specified period.
- Adequate repair facilities are available to commence repairs promptly, without any delay.

b) Notations:
-  : Denotes the system concerned is working at its full capacity state.
-  : Denotes the system concerned is working at reduced capacity state.
-  : Denotes the system concerned is working at failed state.

- A, Bi, C, D: Indicate that the subsystems are in a fully functioning condition.
- a, b, c, d: Denotes that subsystems A, Bi, C, and D are in a state of failure.
- P0(t): Probability of the system operating at full capacity at time t.
- P1(t) – P5(t): Probabilities associated with the system operating in a state of reduced capacity.
- P6(t) – P29(t): Probabilities of the system in failed state.
- ϱi,i=1-4: Average failure rates for subsystems A, Bi, C, and D, respectively.
- μi, i=1-4: Average repair rates for subsystems A, Bi, C, and D, respectively.
- d/dt : Characterizes derivative with respect to time (t).

The diagram illustrating the transitions between states of Veneer Layup System is given in Figure 1. In which state 0 denotes the working of system with full capacity, states 1,2,3,4 and 5 are working of systems with reduced capacity and states 6 – 29 have failed.

IV. Performance Modeling of System

The performance modeling for Veneer Layup System is carried out by Markov Birth-Death Process using a probabilistic approach and a differential equation related to the transition diagram. In performance modeling using Markov analysis, systems are depicted as transitioning between various states based on predefined probabilities. Initially, states representing different configurations or conditions of the system are identified.

These transitions are quantified through transition probabilities, reflecting the likelihood of moving from one state to another within a defined timeframe. Constructing a transition matrix encapsulates these probabilities, facilitating analysis of system behavior. Through this model, metrics like steady-state probabilities or mean time to absorption can be calculated, offering insights into system performance. These equations are determined to describe the steady-state performability of the system.

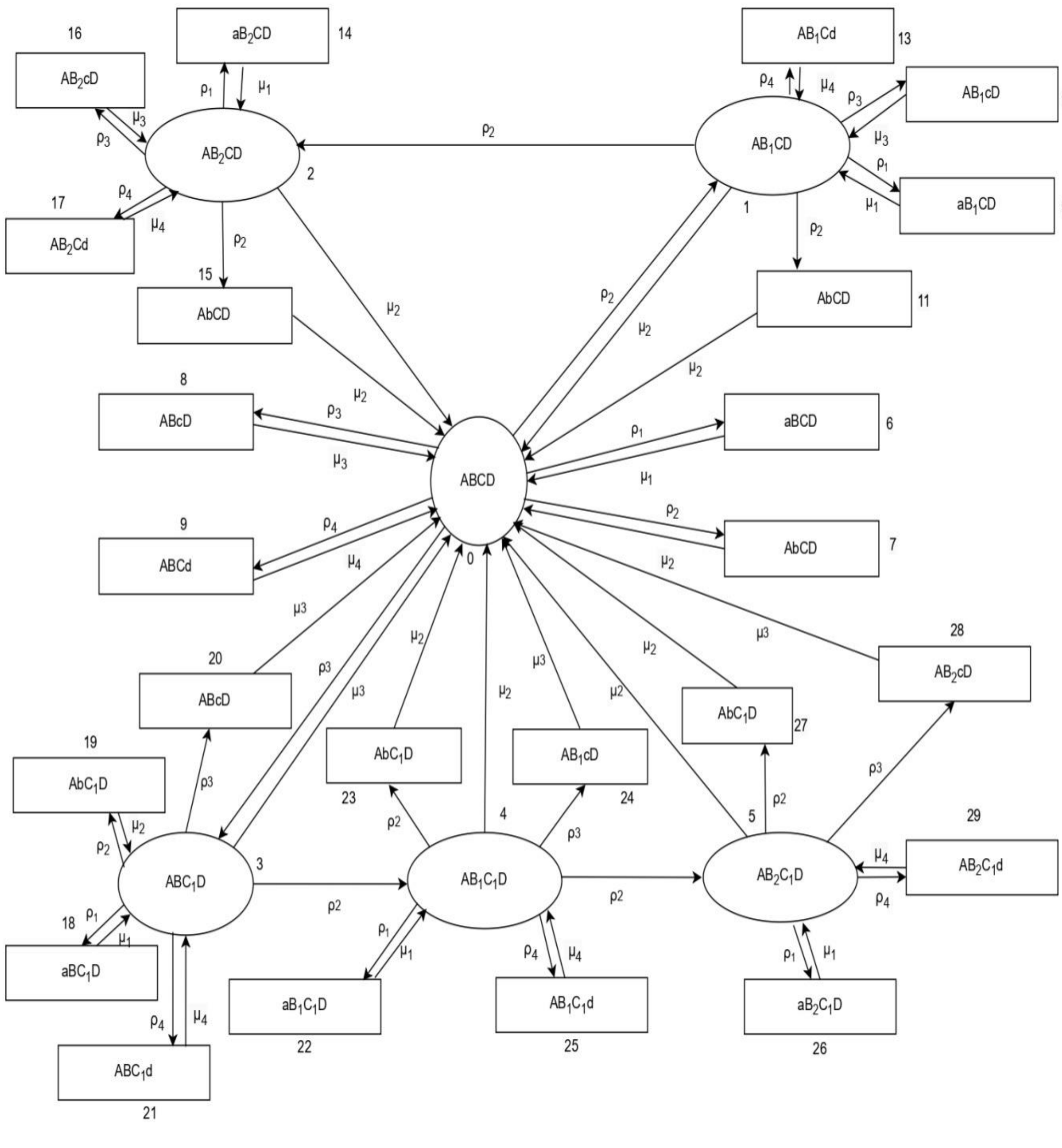


Figure 2: *Performance Model of Veneer Cutting System of Plywood Industry*

V. Performance Analysis

A system's first-order differential equations associated to the transition diagram (Figure 2) at time (t+Δt), can be expressed as follows using the mnemonic rule:

$P_0(t+\Delta t) - P_0(t) = [-\varrho_1\Delta t - 2\varrho_2\Delta t - 2\varrho_3\Delta t - \varrho_4\Delta t]P_0(t) + \mu_2P_1(t)\Delta t + \mu_2P_2(t)\Delta t + \mu_3P_3(t)\Delta t + \mu_2P_4(t)\Delta t + \mu_2P_5(t)\Delta t + \mu_1P_6(t)\Delta t + \mu_2P_7(t)\Delta t + \mu_3P_8(t)\Delta t + \mu_4P_9(t)\Delta t + \mu_2P_{11}(t)\Delta t + \mu_2P_{15}(t)\Delta t + \mu_2P_{20}(t)\Delta t + \mu_3P_{24}(t)\Delta t + \mu_2P_{27}(t)\Delta t + \mu_3P_{28}(t)\Delta t$ (1)

After dividing both sides by Δt, the outcome is:

$[P_0(t+\Delta t) - P_0(t)]/\Delta t = [-\varrho_1-2\varrho_2-2\varrho_3-\varrho_4]P_0(t) + \mu_2P_1(t) + \mu_2P_2(t) + \mu_3P_3(t) + \mu_2P_4(t) + \mu_2P_5(t) + \mu_1P_6(t) + \mu_2P_7(t) + \mu_3P_8(t) + \mu_4P_9(t) + \mu_2P_{11}(t)+\mu_2P_{15}(t)+ \mu_2P_{20}(t)+ \mu_3P_{24}(t)+ \mu_2P_{27}(t) +\mu_3P_{28}(t)$ (2)

After assuming that Δt→0 is the limit, this can be found as:

$P'_0(t)= -X_0P_0(t) + \mu_2P_1(t) + \mu_2P_2(t) + \mu_3P_3(t) + \mu_2P_4(t) + \mu_2P_5(t) + \mu_1P_6(t) + \mu_2P_7(t) + \mu_3P_8(t) + \mu_4P_9(t) + \mu_2P_{11}(t) + \mu_2P_{15}(t) + \mu_2P_{20}(t) + \mu_3P_{24}(t) + \mu_2P_{27}(t) + \mu_3P_{28}(t)$

or

$P'_0(t) + X_0P_0(t) = \mu_2P_1(t) + \mu_2P_2(t) + \mu_3P_3(t) + \mu_2P_4(t) + \mu_2P_5(t) + \mu_1P_6(t) + \mu_2P_7(t) + \mu_3P_8(t) + \mu_4P_9(t) + \mu_2P_{11}(t) + \mu_2P_{15}(t) + \mu_2P_{20}(t) + \mu_3P_{24}(t) + \mu_2P_{27}(t) + \mu_3P_{28}(t)$ (3)

Similarly

$P'_1(t) + X_1P_1(t) = \varrho_2P_0(t) + \mu_1P_{10}(t) + \mu_3P_{12}(t) + \mu_4P_{13}(t)$ (4)

$P'_2(t) + X_2P_2(t) = \varrho_2P_1(t) + \mu_1P_{14}(t) + \mu_3P_{16}(t) + \mu_4P_{17}(t)$ (5)

$P'_3(t) + X_3P_3(t) = \varrho_3P_0(t) + \mu_1P_{18}(t) + \mu_2P_{19}(t) + \mu_4P_{21}(t)$ (6)

$P'_4(t) + X_4P_4(t) = \varrho_2P_3(t) + \mu_1P_{22}(t) + \mu_4P_{25}(t)$ (7)

$P'_5(t) + X_5P_5(t) = \varrho_2P_4(t) + \mu_1P_{26}(t) + \mu_4P_{29}(t)$ (8)

Where

$X_0 = \varrho_1+2\varrho_2+2\varrho_3+\varrho_4$

$X_1 = \varrho_1+2\varrho_2+\varrho_3+\varrho_4+\mu_2$

$X_2 = \varrho_1+\varrho_2+\varrho_3+\varrho_4+\mu_2$

$X_3 = \varrho_1+2\varrho_2+\varrho_3+\varrho_4+\mu_3$

$X_4 = \varrho_1+2\varrho_2+\varrho_3+\varrho_4+\mu_2$

$X_5 = \varrho_1+\varrho_2+\varrho_3+\varrho_4+\mu_2$

$P'_6(t) +\mu_1P_6(t) = \varrho_1P_0(t)$ (9)

$P'_7(t) + \mu_2P_7(t) = \varrho_2P_0(t)$ (10)

$P'_8(t) + \mu_3P_8(t) = \varrho_3P_0(t)$ (11)

$P'_9(t) + \mu_4P_9(t) = \varrho_4P_0(t)$ (12)

$P'_{10}(t) + \mu_1P_{10}(t) = \varrho_1P_1(t)$ (13)

$P'_{11}(t) + \mu_2P_{11}(t) = \varrho_2P_1(t)$ (14)

$P'_{12}(t) + \mu_3P_{12}(t) = \varrho_3P_1(t)$ (15)

$P'_{13}(t) + \mu_4P_{13}(t) = \varrho_4P_1(t)$ (16)

$P'_{14}(t) + \mu_1P_{14}(t) = \varrho_1P_2(t)$ (17)

$P'_{15}(t) + \mu_2P_{15}(t) = \varrho_2P_2(t)$ (18)

$P'_{16}(t) + \mu_3P_{16}(t) = \varrho_3P_2(t)$ (19)

$P'_{17}(t) + \mu_4P_{17}(t) = \varrho_4P_2(t)$ (20)

$P'_{18}(t) + \mu_1P_{18}(t) = \varrho_1P_3(t)$ (21)

$P'_{19}(t) + \mu_2P_{19}(t) = \varrho_2P_3(t)$ (22)

$P'_{20}(t) + \mu_3P_{20}(t) = \varrho_3P_3(t)$ (23)

$P'_{21}(t) + \mu_4P_{21}(t) = \varrho_4P_3(t)$ (24)

$P'_{22}(t) + \mu_1P_{22}(t) = \varrho_1P_4(t)$ (25)

$P'_{23}(t) + \mu_2P_{23}(t) = \varrho_2P_4(t)$ (26)

$P'_{24}(t) + \mu_3P_{24}(t) = \varrho_3P_4(t)$ (27)

$P'_{25}(t) + \mu_4P_{25}(t) = \varrho_4P_4(t)$ (28)

$P'_{26}(t) + \mu_1P_{26}(t) = \varrho_1P_5(t)$ (29)

$P'_{27}(t) + \mu_2P_{27}(t) = \varrho_2P_5(t)$ (30)

$P'_{28}(t) + \mu_3 P_{28}(t) = \varrho_3 P_5(t)$ (31)

$P'_{29}(t) + \mu_4 P_{29}(t) = \varrho_4 P_5(t)$ (32)

It is a complex system, and every system must be accessible for a long time to achieve the maximum output. The steady-state behavior of the plywood plant can be investigated by finding $t \to \infty$, — $\to 0$.

With this, equations from (01) to (32) reduced to

$X_0 P_0(t) = \mu_2 P_1(t) + \mu_2 P_2(t) + \mu_3 P_3(t) + \mu_2 P_4(t) + \mu_2 P_5(t) + \mu_1 P_6(t) + \mu_2 P_7(t) + \mu_3 P_8(t) + \mu_4 P_9(t) + \mu_2 P_{11}(t) + \mu_2 P_{15}(t) + \mu_2 P_{20}(t) + \mu_3 P_{24}(t) + \mu_2 P_{27}(t) + \mu_3 P_{28}(t)$ (33)

Similarly

$X_1 P_1(t) = \varrho_2 P_0(t) + \mu_1 P_{10}(t) + \mu_3 P_{12}(t) + \mu_4 P_{13}(t)$ (34)

$X_2 P_2(t) = \varrho_2 P_1(t) + \mu_1 P_{14}(t) + \mu_3 P_{16}(t) + \mu_4 P_{17}(t)$ (35)

$X_3 P_3(t) = \varrho_3 P_0(t) + \mu_1 P_{18}(t) + \mu_2 P_{19}(t) + \mu_4 P_{21}(t)$ (36)

$X_4 P_4(t) = \varrho_2 P_3(t) + \mu_1 P_{22}(t) + \mu_4 P_{25}(t)$ (37)

$X_5 P_5(t) = \varrho_2 P_4(t) + \mu_1 P_{26}(t) + \mu_4 P_{29}(t)$ (38)

$\mu_i P_j(t) = \varrho_i P_0(t)$, where, i=1,2,3,4; j= 6,7,8,9 (39)

$\mu_i P_j(t) = \varrho_i P_1(t)$, where, i=1,2,3,4; j= 10,11,12,13 (40)

$\mu_i P_j(t) = \varrho_i P_2(t)$, where, i=1,2,3,4; j= 14,15,16,17 (41)

$\mu_i P_j(t) = \varrho_i P_3(t)$, where, i=1,2,3,4; j= 18,19,20,21 (42)

$\mu_i P_j(t) = \varrho_i P_4(t)$, where, i=1,2,3,4; j= 22,23,24,25 (43)

$\mu_i P_j(t) = \varrho_i P_5(t)$, where, i=1,2,3,4; j= 26,27,28,29 (44)

By solving these equations as:

Taking K as a constant, which is the ratio of failure rate to repair rate,

K = –

K_1= —, K_2= —, K_3= —, K_4= —, K_5 = ————, K_6 = ————,

K_7=————, K_8=————, K_9=————

$P_1 = K_8 P_0$ (45)

$P_2 = K_8 K_9 P_0$ (46)

$P_3 = K_5 P_0$ (47)

$P_4 = K_5 K_6 P_0$ (48)

$P_5 = K_5 K_6 K_7 P_0$ (49)

$P_6 = K_1 P_0$ (50)

$P_7 = K_2 P_0$ (51)

$P_8 = K_3 P_0$ (52)

$P_9 = K_4 P_0$ (53)

$P_{10} = K_1 K_8 P_0$ (54)

$P_{11} = K_2 K_8 P_0$ (55)

$P_{12} = K_3 K_8 P_0$ (56)

$P_{13} = K_4 K_8 P_0$ (57)

$P_{14} = K_1 K_8 K_9 P_0$ (58)

$P_{15} = K_2 K_8 K_9 P_0$ (59)

$P_{16} = K_3 K_8 K_9 P_0$ (60)

$P_{17} = K_4 K_8 K_9 P_0$ (61)

$P_{18} = K_1 K_5 P_0$ (62)

$P_{19} = K_2 K_5 P_0$ (63)

$P_{20} = K_3 K_5 P_0$ (64)

$P_{21} = K_4 K_5 P_0$ (65)

$P_{22} = K_1 K_5 K_6 P_0$ (66)

$P_{23}= K_2K_5K_6P_0$ (67)
$P_{24}= K_3K_5K_6P_0$ (68)
$P_{25}= K_4K_5K_6P_0$ (69)
$P_{26}= K_1K_5K_6K_7P_0$ (70)
$P_{27}= K_2K_5K_6K_7P_0$ (71)
$P_{28}= K_3K_5K_6K_7P_0$ (72)
$P_{29}= K_4K_5K_6K_7P_0$ (73)

In accordance with the normalization principle, the sum of collective probabilities of all events should be equal to one that is:

$$\Sigma P_i = 1 \quad (74)$$

$P_0+P_1+P_2+ \ldots + P_{29} = 1$ (75)

$P_0[1+(K_8+K_8K_9+K_5+K_5K_6+K_5K_6K_7+K_1+K_2+K_3+K_4+K_1K_8+K_2K_8+K_3K_8+K_4K_8+K_1K_8K_9+K_2K_8K_9+K_3K_8K_9+K_4K_8K_9+K_1K_5+K_2K_5+K_3K_5+K_4K_5+K_1K_5K_6+K_2K_5K_6+K_3K_5K_6+K_4K_5K_6+K_1K_5K_6K_7+K_2K_5K_6K_7+K_3K_5K_6K_7+K_4K_5K_6K_7)]= 1$

or

$P_0=1/[1+(K_8+K_8K_9+K_5+K_5K_6+K_5K_6K_7+K_1+K_2+K_3+K_4+K_1K_8+K_2K_8+K_3K_8+K_4K_8+K_1K_8K_9+K_2K_8K_9+K_3K_8K_9+K_4K_8K_9+K_1K_5+K_2K_5+K_3K_5+K_4K_5+K_1K_5K_6+K_2K_5K_6+K_3K_5K_6+K_4K_5K_6+K_1K_5K_6K_7+K_2K_5K_6K_7+K_3K_5K_6K_7+K_4K_5K_6K_7)]$ (76)

Now, the system availability $A(\infty)$ can be found by using:

$A(\infty) = P_0+P_1+P_2+P_3+P_4+P_5$
$= [1+K_8+K_8K_9+K_5+K_5K_6+K_5K_6K_7]P_0$ (77)

Using equation 77, the long-term availability for a range of permissible combinations of veneer manufacturing systems' failure and repair rates in a steady state can be ascertained. Table 1 providesan overview of how failure and repair rates affect the availability of the system. Availability impacts system performance by ensuring that each part of the system is ready to work when desired.

Table 1: *Failure and Repair Rates of Veneer System*

Sub-System's Name	Mean Failure Rate (ϱ_i)	Mean Repair Rate (μ_i)
Debarking Machine (A)	0.013 (ϱ_1)	0.15 (μ_1)
Veneer Cutting Machine (B)	0.004 (ϱ_2)	0.2 (μ_2)
Veneer Drier (C)	0.0024 (ϱ_3)	0.126 (μ_3)
Gluing and Pasting (D)	0.005 (ϱ_4)	0.19 (μ_4)

Table 2 and Figure 3 describe the effect of different failure and repair rates of a debarking machine on system performance, in terms of availability. It is observed that as the failure rate increases from 0.003 to 0.043, the system's performability declines from 0.8886 to 0.5194, marking a decrease of 41.5%. Likewise, with the repair rate increasing from 0.05 to 0.45, the system's performability improves from 0.8886 to 0.9328, reflecting a 4.7% increase.

Table 2: *Effect of the Failure and Repair Rates of Debarking Machine subsystem on system Performability(%)*

Failure Rates (ϱ_1)	Repair Rates of Debarking Machine (μ_1)					Constant Parameters
	0.05	0.15	0.25	0.35	0.45	
0.003	0.8886	0.9214	0.9282	0.9312	0.9328	$\varrho_2 = 0.004$,
0.013	0.7545	0.8680	0.8950	0.9070	0.9139	$\mu_2 = 0.2$,
0.023	0.6556	0.8205	0.8640	0.8841	0.8957	$\varrho_3 = 0.0024$,
0.033	0.5796	0.7780	0.8352	0.8623	0.8782	$\mu_3 = 0.126$, $\varrho_4 = 0.005$,
0.043	0.5194	0.7396	0.8082	0.8416	0.8614	$\mu_4 = 0.19$

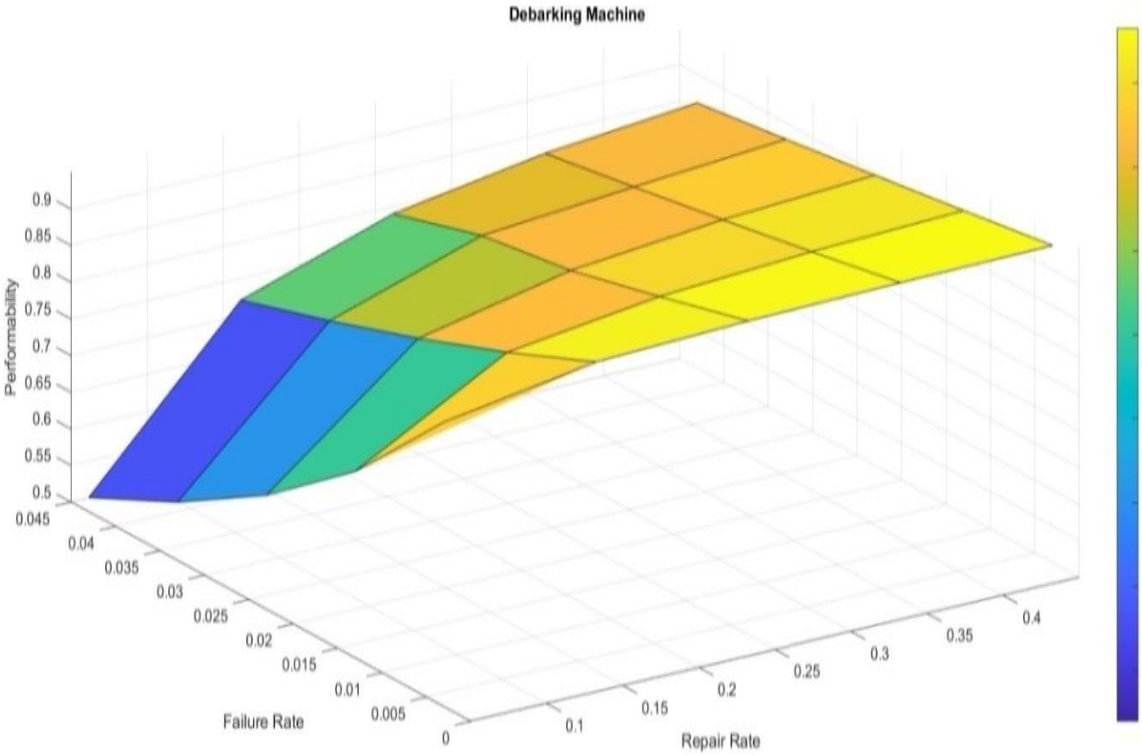


Figure 3: *Performability Variation with respect to Failure and Repair Rates of Debarking Machine Subsystem*

Similarly, in Table 3 and Figure 4 for the Veneer Cutting Machine subsystem, the performance of the subsystem in terms of availability varies between 3.35% and 1.175% for the respective failure (ϱ_2) and repair rates (μ_2) when all other factors stay the same.

Table 3: *Effect of the Failure and Repair Rates of Veneer Cutting Machine Subsystem on System Performability (%)*

Failure Rates (ϱ_2)	Repair Rates of Veneer Cutting Machine (μ_2)					Constant Parameters
	0.1	0.15	0.2	0.25	0.3	
0.002	0.8680	0.8731	0.8756	0.8772	0.8782	$\varrho_1 = 0.013$,
0.003	0.8606	0.8680	0.8718	0.8741	0.8756	$\mu_1 = 0.15$,
0.004	0.8532	0.8630	0.8680	0.8711	0.8731	$\varrho_3 = 0.0024$,
0.005	0.8460	0.8581	0.8643	0.8680	0.8706	$\mu_3 = 0.126$, $\varrho_4 = 0.005$,
0.006	0.8389	0.8532	0.8606	0.8650	0.8680	$\mu_4 = 0.19$

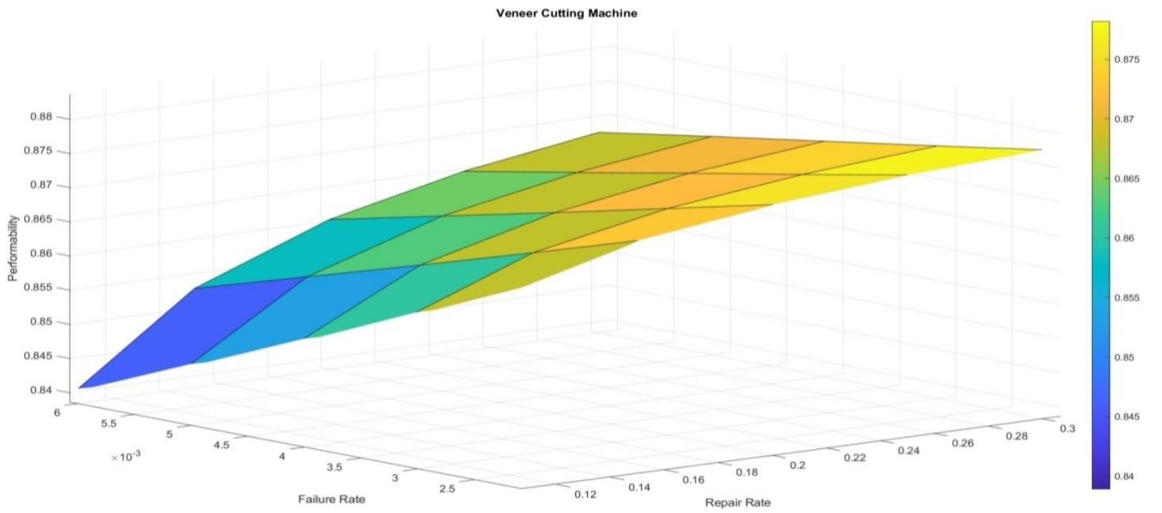


Figure 4: *Performability Variation with respect to Failure and Repair Rates of Veneer Cutting Machine Subsystem*

Table 4 and Figure 5 illustrate the impact of repair and failure rates of the Veneer Drier subsystem on its performability. It is observed that the known values of failure rate ($\varrho 3$) and repair rate ($\mu 3$) of Veneer drier, as the failure rate increases from 0.0012 to 0.0036, and the performability of the system decreases quickly from 0.8739 to 0.8569, i.e., 1.945%. Also, as the repair rate ($\varrho 3$) increases from 0.106 to 0.146, the performability of the system increases considerably from 0.8739 to 0.8763, i.e., 0.28%.

Table 4: *Effect of the Failure and Repair Rates for Veneer Drier Subsystem on System Performability(%)*

Failure Rates (ϱ_3)	Repair Rates of Veneer Drier (μ_3)					Constant Parameters
	0.106	0.116	0.126	0.136	0.146	
0.0012	0.8739	0.8746	0.8753	0.8758	0.8763	$\varrho_1 = 0.013$, $\mu_1 = 0.15$, $\varrho_2 = 0.004$, $\mu_2 = 0.2$, $\varrho_4 = 0.005$, $\mu_4 = 0.19$
0.0018	0.8696	0.8707	0.8716	0.8724	0.8731	
0.0024	0.8653	0.8668	0.8680	0.8691	0.8700	
0.0030	0.8611	0.8629	0.8645	0.8658	0.8669	
0.0036	0.8569	0.8591	0.8609	0.8625	0.8638	

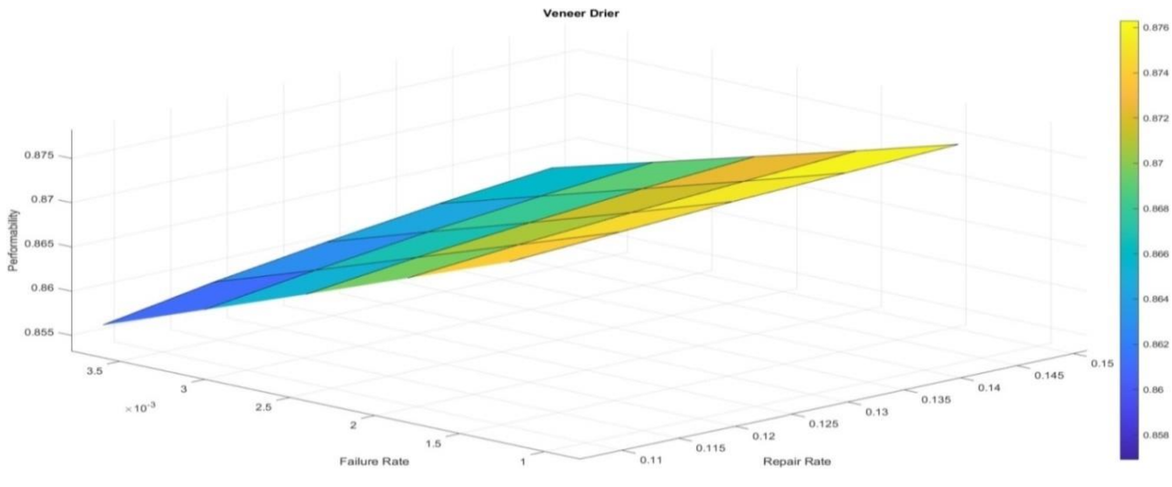


Figure 5: *Performability Variation with respect to Failure and Repair Rates of Veneer Driers Subsystem*

In the Table 5 and Figure 6 describe various combinations of repair and failure rates for gluing and pasting subsystem that influence their performability. It's clearly shown that for distinct values of failure rate (ϱ_4) and repair rate (μ_4), when the failure rate increases from 0.001 to 0.009, then performability decreases from 0.8729 to 0.7659 i.e. 12.26%. In the same way as the repair rate increases from 0.05 to 0.33, gluing and pasting performability increases drastically from 0.8729 to 0.8859 i.e. (1.49%).

Table 5: *Effect of the Failure and Repair Rates of Gluing and Pasting Subsystem on System Performability(%)*

Failure Rates	Repair Rates of Gluing and Pasting					Constant Parameters
	0.05	0.12	0.19	0.26	0.33	
0.001	0.8729	0.8818	0.8842	0.8853	0.8859	$\varrho_1 = 0.013$,
0.003	0.8434	0.8690	0.8760	0.8793	0.8812	$\mu_1 = 0.15$,
0.005	0.8159	0.8566	0.8680	0.8734	0.8765	$\varrho_2 = 0.004$, $\mu_2 = 0.2$,
0.007	0.7901	0.8446	0.8602	0.8676	0.8719	$\varrho_3 = 0.0024$,
0.009	0.7659	0.8328	0.8525	0.8618	0.8673	$\mu_3 = 0.126$

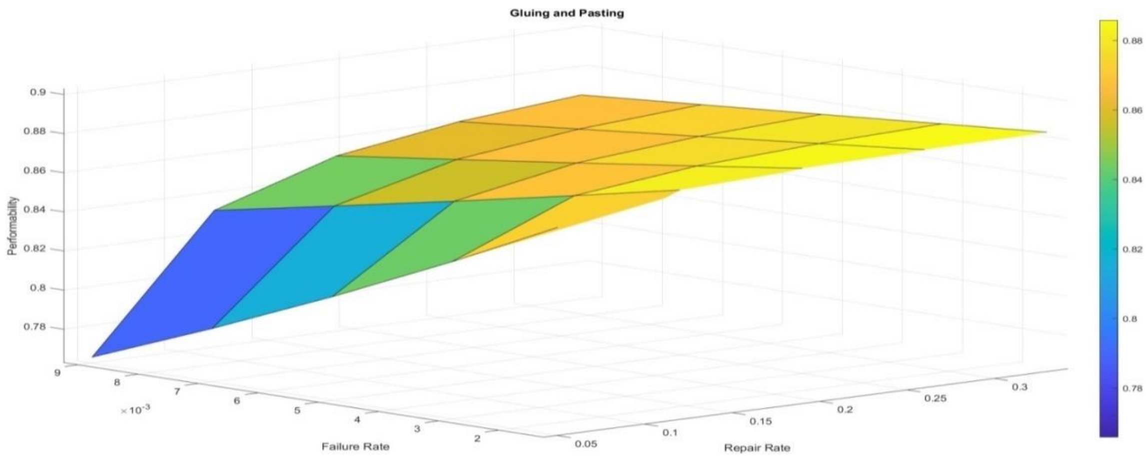


Figure 6: *Performability Variation with respect to Failure and Repair Rates of Gluing and Pasting Subsystem*

VI. Results

This paper explores the application of Markov techniques to evaluate the performance of production system in the plywood industry by providing DSS regarding maintainability order. According to Table 6, the study indicates that the Veneer Drier subsystem contributes the least to the system's performance, while the Debarking Machine subsystem is the most critical subsystem of the assembly line system.

Table 6: *Effect of Subsystems Failure and Repair Rates Deviation on System Performance*

Name of Sub-System	Variation in Failure Rates ϱ_i, (Repair Rates μ_i)	Impact of Variation on System Performance (%)	Proposed Maintenance Priority
Debarking Machine (A)	0.003-0.043, (0.05-0.45)	0.9328-0.5194 (44.318%)	I
Gluing and Pasting (D)	0.00-0.009, (0.05-0.33)	0.8859-0.7659 (13.546%)	II
Veneer Cutting Machine (B)	0.002-0.006, (0.1-0.3)	0.8782-0.8389 (4.475%)	III
Veneer Drier (C)	0.0012-0.0036, (0.106-0.146)	0.8763-0.8569 (2.214%)	IV

The Markov approach is used to analyze the performance in terms of availability. If there is a need to increase the performability of such systems, it should be recommended to enhance the system performance using optimization techniques like Ant Colony Algorithm, PSO and Teacher Learning Based Optimization etc.

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