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Markov Decision Process approach in the estimation of raw material quality in incoming inspection process

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Abstract. The incoming inspection process in any manufacturing plant aims to control quality, reduce manufacturing costs, eliminate scrap, and process failure downtime due to defective raw materials. Prediction of the raw material acceptance rate can regulate the raw material supplier selection and improve the manufacturing process by filtering out non-conformities. This paper presents a raw material acceptance prediction model (RMAP) developed based on the Markov analysis. RFID tags are used to track the parts throughout the process. A secondary dataset can be derived from the raw RFID data. In this study, a dataset is simulated to reflect a typical incoming inspection process consisting of six substations (Packaging Inspection, Visual Inspection, Gauge Inspection, Rework1, and Rework2) are considered. The accepted parts are forwarded to the Pack and Store station and stored in the warehouse. The non-conforming parts are returned to the supplier. The proposed RMAP model estimates the probability of the raw material being accepted or rejected at each inspection station. The proposed model is evaluated using three test cases: case A (lower conformities), case B (higher conformities) and case C (equal chances of being accepted and rejected). Based on the outcome of the limiting matrix for the three test cases, the results are discussed. The steady-state matrix forecasts the probability of the raw material in a random state. This prediction and forecasting ability of the proposed model enables the industries to save time and cost.

1. Introduction

Materials purchased from providers and then utilized as inputs to the manufacturing process are referred to as raw materials in the inventory. Raw material management reduces production stoppages by having the appropriate quantity of material put in the proper location in the raw material inventory at the right time at a reasonable cost. These expenses can be kept as low as feasible with proper management, and material flow can be linked with production [1].

Companies use inventory management to maintain a competitive advantage, stay in business, and grow their market share. It has been determined that inventory management accounts for 30-35 % of the material value [2].

Inventory, according to Taiichi Ohno, is one of the seven wastes that should be avoided. The most visible component of a company's overall assets, it accounts for 5-30 % of total assets [3]. It is important to develop a model that fulfils companies' varied material management demands of companies cost-effectively.

One of the most significant wastes in lean manufacturing is a defect. A poor procedure or a defective raw material can both cause product faults. Reducing takt time and enabling Lean manufacturing could be accomplished by addressing raw material faults at the manufacturing process.

Quality endurance includes the inbound inspection procedure and verifies that the raw material quality meets the agreed-upon requirements between the vendor and the buyer. This human-centric process has been automated in modern times employing various competitive technologies, with Radio Frequency Identification (RFID) deployment being one of the first. RFID tags are a significant advancement in the field of automated identification systems. Intelligent bar codes, or RFID tags, have a chip that records information about the goods. An RFID reader is used to read these tags and thus enables the tracking of objects. This technology was originally designed to track cattle, but their applications have subsequently broadened towards vehicle tracking [4], pets [5], and items in the manufacturing process [6]. Modelling manufacturing processes that include humans can result in erroneous findings. When examining a highly manual process, a study by [7] investigated improving the inaccuracies in discrete event modelling. Decision models use the data log from these RFID readers better understand the process parameters. The Markov Decision Process is one such model.

Markov chains and Markov processes model stochastic processes and are classified as Discrete-time and continuous-time processes. They mathematically depict a process by showing its likelihood of moving between phases. This study's goal was to help assure right-first-time production. This study related discrete event simulations to human performance models. Each station contains RFID readers, and the raw materials passing through them have RFID tags.

The balance of the paper is divided into parts. Section 2.1 describes the incoming inspection case study, and the substation decomposition is explained in 2.2. The Markov chain, Markov process and the stochastic process are detailed in Section 2.3. Estimation of Transition Matrix is elaborated in Section 2.4. The proposed raw material acceptance prediction model (RMAP) model is used to estimate the probability of the acceptance and rejection of the raw materials are detailed in Section 2.5. Section 2.6 examines the predicting of raw material at random, while Section 3 discusses the suggested model's outcomes, and the findings are concluded in Section 5.

2. Model Development

A quality prediction model is developed based on the RFID data captured in an automotive manufacturing pipeline. In a typical automotive manufacturing plant, the substations are installed with an RFID reader, which logs the parts traversing through the substations. The data from the RFID reader is taken as a raw dataset. Based on the daily performance, the weights are estimated for Markov analysis is detailed in section 2.6.

2.1. Incoming Inspection Case study

The process flow diagram of the incoming inspection station of an automotive supply chain environment is shown in Figure 1. The workstation contains seven sub-sections packaging inspection, visual inspection, gauge inspection, rework station 1, rework station 2, return, pack and store. The material received from the supplier is expected to meet the specified material standards. The material undergoes a series of visual and dimensional checks for qualification.

The functions of the seven substations and their process are explained visually in Figure 1. For minor changes, the materials will be subject to corrections in rework stations. Upon corrections at rework 1 and rework 2, the materials will be sent for inspection at visual inspection and gauge inspection, respectively. The minor defects are addressed and re-inspected at respective substations. When the defects are irreparable, the materials are returned to the vendor through the return gateway substation.

The raw materials are unloaded at the incoming bay. The package is checked for its adherence to the specified packaging standards regarding a signed Packaging and Delivery Standard (PDS) document by the experts from both parties. The packages that do not abide by the standards are returned to the vendor, and the inventory is updated accordingly. The accepted packages are sent for visual inspection.

At Visual inspection, the skilled professional unboxes the material from the package and checks for colour, texture, and appearance conditions with the master sample. The materials with minor deformities are sent for rework. The reworked materials are re-inspected. Upon qualifying, they are sent to the next stage, where the dimensions are checked. The materials with irreparable changes after rework are returned to the vendor. The materials with major deformations are also returned to the vendor. The reworked and the returned materials are updated in the inventory accordingly.

The visually qualified materials are passed to gauges to check if it meets the specified dimension with tolerance. This process is very much necessary to address the fit and finish issues with mating parts. The OK parts are packed and stored at the warehouse for future use. Whereas the major non-conformities are returned, while the minor non-conformities are reworked and rechecked for acceptance. The reworked returned and OK conditions of the materials are updated accordingly in the inventory.

2.2. Finite State Machine Decomposition

A finite state machine (FSM) diagram decomposes the seven substations of the input inspection. Each substation is a state and is represented in a state machine diagram, as shown in Figure 1.
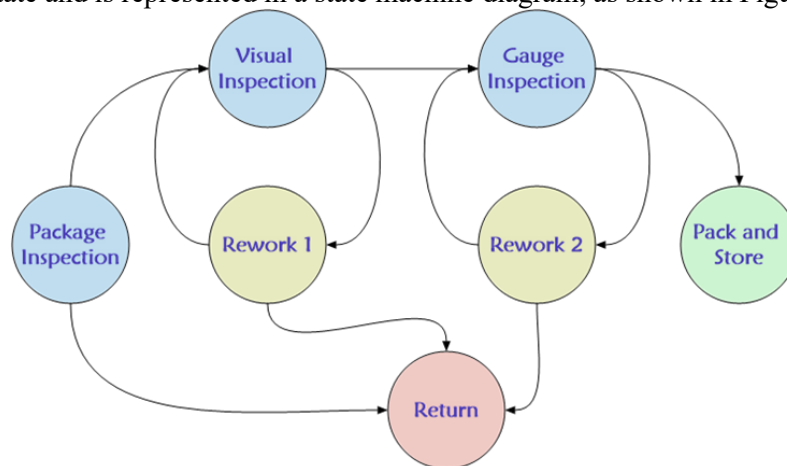

Figure 1. Finite state machine diagram of the seven substations.

The FSM model developed contains seven states. The transition of the states from one state to the other is represented using arrows. During the transition to the next state, only the current state and the input are considered, whereas; the previous state is not considered. The complete transition of each sub-state, along with the description, is tabulated in Table 1. The outcome of each transition is expressed in the output column.

Table 1. State transition of the incoming inspection of raw material.

	Previous	*Current*	*Input*	*Next*	*Output*	*Description*
PI	-	PI	OK	VI	Conformities	Move to VI
	-	PI	Not OK	RT	Error in packaging	Return to supplier
VI	PI	VI	OK	GI	Conformities	Move to GI
	PI	VI	Not OK	RW1	Minor change	Send to Rework
	RW1	VI	OK	GI	Conformities	Move to GI
	RW1	VI	Not OK	RT	Nonconformities	Return to Supplier

GI	VI	GI	OK	PS	Conformities	Pack and store
	VI	GI	Not OK	RW2	Minor change	Send to Rework
	RW2	GI	OK	PS	Conformities	Pack and Store
	RW2	GI	Not OK	RT	Nonconformities	Return to supplier
RW1	VI	RW1	OK	VI	Minor correction	Move to VI
	VI	RW1	Not OK	RT	Major change	Return to Supplier
RW2	GI	RW2	OK	GI	Minor correction	Move to GI
	GI	RW2	Not OK	RT	Major change	Return to Supplier
PS	GI	PS	OK	-	Conformities	Finish
RT	-	RT	OK	-	Nonconformities	Return to Supplier

2.3. Markov Process / Markov chain for incoming Inspection

The functions in the substations are explained using a finite state machine diagram. Further, the functions are converted into a Markov chain. A discrete-valued Markov process is known as a Markov chain. The state-space of potential Markov chain values is finite or quantifiable when the chain is discrete-valued. A Markov process is a stochastic process in which the process's history is irrelevant if the system's present state is known. The current state has all knowledge about the past and present that may predict the future [8 -13]. The Markov model is the one in which the present state is solely dependent on the preceding state thus.

$$p\left(S_n / S_{n-1}, S_{n-2}, ...\right) = p\left(S_n = s_n / S_{n-1} = s_{n-1}\right);$$

$$s_n \in S = \{s_1, s_2, ... s_M\} \tag{1}$$

depicts a well-known Markov chain or first-order Markov chain. Furthermore, if transition probabilities are independent of time 'n' thus,

$$P\{S_n = s_n \mid S_{n-1} = s_{n-1}\} = P\{S_2 = s_2 \mid S_1 = s_1\}, \forall s_n \in X \tag{2}$$

2.3.1. Stochastic Process and Markov chain

The study of how a random variable changes over time is known as a stochastic process. The stochastic process through which the system's state may be monitored at discrete points in time refers to the discrete-time stochastic process. In a continuous-time, stochastic process, the system's state may be seen at any moment.

An s x s matrix depicts the transition probability.

$$P = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1s} \\ p_{21} & p_{22} & \cdots & p_{2s} \\ \vdots & \vdots & \ddots & \vdots \\ p_{s1} & p_{s2} & \cdots & p_{ss} \end{pmatrix}$$

Each row's probability must add up to 1, i.e., for each i

$$\sum_{j=1}^{j=s} p_{ij} = 1$$

$$P = \begin{array}{c} \\ PI \\ VI \\ GI \\ RW1 \\ RW2 \\ RT \\ PS \end{array} \begin{bmatrix} PI & VI & GI & RW1 & RW2 & RT & PS \\ 0 & 1/2 & 0 & 0 & 0 & 1/2 & 0 \\ 0 & 0 & 1/2 & 1/2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1/2 & 0 & 1/2 \\ 0 & 1/2 & 0 & 0 & 0 & 1/2 & 0 \\ 0 & 0 & 1/2 & 0 & 0 & 1/2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

2.3.2. Initial probability distribution

The raw material enters the factory after quality inspection. At the inspection bay, every material is checked for its packaging standards as per the PDS. The state flow diagram with transition probabilities is depicted in Figure 2. Only if the material conforms with the PDS, the material is taken for the next step of quality checking. So, the only entry point to the raw material is Packaging inspection (PI), So the initial distribution probability P0 is given by

$$P0 = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$
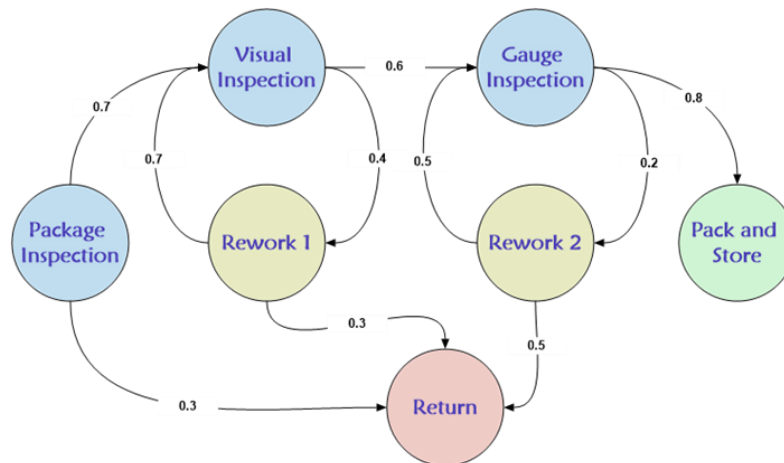

Figure 2. State flow diagram with transition probabilities.

2.4. Transition Matrix

In engineering, operations research and time series, Markov models are frequently used. It is utilized to explain transitions between states in an automotive assembly supply chain's arriving inspection station in this work. A transition matrix (P) is a matrix in which the number of states is represented by the letter 'n'. The transition probability of the Markov process is used to create the matrix. The chances of transitioning from state 'j' to 'i' are equal to each element in the transition matrix 'P_{ij}' which is depicted as an '$n \times n$' matrix. Therefore $0 \leq P_{ij} \leq 1$ must be true for all 'i' and 'j'. Consider the state machine diagram shown in Fig 2. The aggregate of the transition probabilities from one state to another state is the total of the entries in a row. As a result, the sum of the row values must be equal to 1. This type of matrix is referred to as a stochastic matrix.

The developed model is computed to estimate the following results.
a. Probability of the raw material being accepted or rejected.
b. Forecasting the probability of the raw material at an arbitrary state
c. Estimate the steady-state probability for the given transition matrix.

2.5. Probability of the raw material being accepted or rejected at each inspection state.

Three test cases were considered to evaluate the proposed model and the weights are tabulated in Table 2. The three test cases are, Case A (lower conformities), Case B (higher conformities) and Case C (equal chances of being accepted and rejected). The following states from the incoming inspection case study are considered: PI, VI, GI, RWI and RW2.

During the intial stages, when the process has just begun, the measurables (Attribute and Variable data) may have large differences from expected and thus the error value. Moving forward, the difference would be soughted out and thus the error would come down to minimum.

Table 2. Test cases A, B and C for raw material acceptance and rejection in each state

State -Action	*Case-A (30/70)*	*Case-B (70/30)*	*Case-C (50/50)*
PI-VI	0.3	0.7	0.5
PI-RT	0.7	0.3	0.5
VI-GI	0.4	0.6	0.5
VI-RWI	0.6	0.4	0.5
GI-RW2	0.8	0.2	0.5
GI-PS	0.2	0.8	0.5
RWI-VI	0.4	0.6	0.5
RW1-RT	0.6	0.4	0.5
RW2-GI	0.2	0.8	0.5
RW2-RT	0.8	0.2	0.5

For each of the above test cases, the limiting matrix is calculated, and the results are discussed in the following section.

3. Results and Discussion

This section presents the results of the model for three scenarios. They were limiting probability to estimate the probability of the raw material being accepted or rejected at each inspection state. N-step probability to forecast the probability of the material at an arbitrary state. To find the steady-state probability for a given transition matrix. The probabilities in each state of raw materials moving to Return and Pack and Store is depicted in Figure 3.
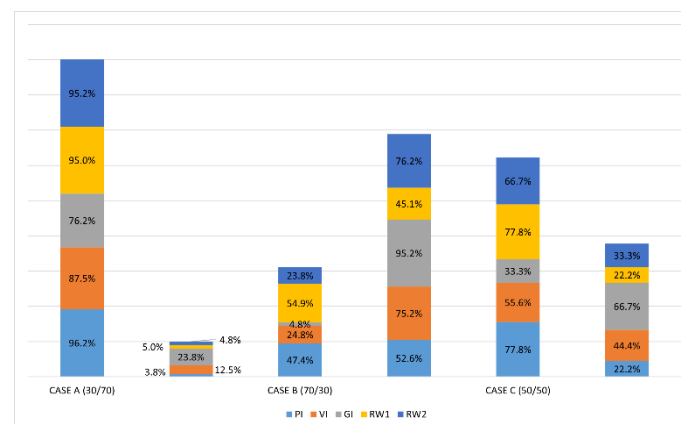

Figure 3. Probabilities in each state of raw materials moving to Return and Pack and Store.

In the long run, 77% of the raw materials would be returned to the supplier for their bad quality and packaging; thereby, only 23% of the raw materials would reach the Pack and Store. This procedure intends to drastically improve the packing quality of the raw material. Almost every chance of the raw material getting accepted and rejected at the visual inspection stage 55% and 45% respectively. Once the material reaches the gauge inspection, there is 64% that the material would get through this checkpoint and reach the desired destination, Pack and Store. Interestingly, there are almost equal chances of the raw material being accepted and rejected (46%) after rework. So, 54% of the parts are of major nonconformities. Table 3 lists the state transitions for the assumed three scenarios.

Table 3. State transition of the incoming inspection of raw material.

States	Case A (30/70)		Case B (70/30)		Case C (50/50)	
	RT	PS	RT	PS	RT	PS
PI	0.9624	0.0376	0.4737	0.5263	0.7778	0.2222
VI	0.8747	0.1253	0.2481	0.7519	0.5556	0.4444
GI	0.7619	0.2381	0.0476	0.9524	0.3333	0.6667
RW1	0.9499	0.0501	0.5489	0.4511	0.7778	0.2222
RW2	0.9524	0.0476	0.2381	0.7619	0.6667	0.3333

4. Conclusion

This paper presented a raw material acceptance prediction model (RMAP) developed based on the Markov analysis. The proposed RMAP model estimates the probability of the raw material being accepted or rejected at each inspection station (Packaging Inspection, Visual Inspection, Gauge Inspection, Rework1, and Rework2). The accepted parts are forwarded to Pack and Store station and stored in the warehouse. The non-conforming parts are returned to the supplier. The incoming inspection process in any manufacturing plant aims to control quality, reduce manufacturing costs, eliminate scrap, and process failure downtimes due to the non-conforming raw materials. Prediction of the raw material acceptance rate can regulate the raw material supplier selection and improves the manufacturing process by filtering out non-conformities. Further to the limiting matrix estimation, the trajectory of every accepted raw material flowing from Packaging Inspection to Pack and Store can be used in ranking the material into subcategories. The ranking of the materials can enable quality output.

Acknowledgements

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