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A predictive data-driven state-dependent decision approach to determine inventory system states for critical spare parts

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Abstract *– The Markov chain is widely used in state-dependent inventory control of spare parts because of its ability to model the gradual degradation process of components and predict their condition. Also, according to previous studies, considering system information causes a significant reduction in costs. Therefore, the present study tries to extract the system information using a machine learning algorithm and provide it as a transition matrix to the Markov decision process (MDP) to determine the future states of the critical spare parts inventory system. In the presented method, the machine learning algorithm, here Adaptive Neuro-Fuzzy Inference System (ANFIS), is in charge of the training data. The Markov chain uses the trained data to predict the future states of the inventory system. For this purpose, four states have been considered, each representing a level of tension and demand in the inventory system. Applying the model to the data collected for a critical component showed that the model has good accuracy in predicting the following states of the system. Also, the presented model offers a lower error rate, RMSE, and MAPE, compared to the ARIMA model for predicting the next state of the inventory system.*

Keywords*– MDP, Machine learning, state-dependent spare parts, ANFIS, Inventory.*

I. INTRODUCTION

Strategic and important spare parts significantly affect how manufacturing units and other machinery operate. The operation and manufacturing process can cease if these components approach their last deterioration phase. Additionally, the stoppage of other machinery due to the failure of one machine in a manufacturing unit might interrupt operation. In this situation, the lack of spare parts can lengthen the stoppage of the production line. Therefore, maintaining a suitable spare part level is one of such systems' obligations. As a result, it can substantially help to make the system interruption time-limited and manageable to replace a malfunctioning component with a functional one (Basten and Houtum 2014). In this situation, the absence of spare components might prolong the time required for the system to change a part; therefore, having replacement parts on hand can accelerate the procedure and lower the cost of downtime. In order to lessen the economic and reputational (loss of brand image) implications of system failure, it is essential for production organizations and service companies to maintain the continuous operation of their systems and necessary infrastructure (Turrini and Meissner, 2017). Therefore, it's imperative to keep sufficient inventory available to prevent expensive downtimes (Lin et al., 2017). Higher storage costs for such components are one of the difficulties that should be considered, even though higher stock levels limit operations failure time(Kiesmüller, 2020). Spare parts are intermittently

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consumed, and various spare parts are stored for this type of inventory (Rubino et al., 2010). The cost of spare components is frequently high. As a result, keeping extra parts in storage might be expensive. As a result, one of the major problems with spare parts management is maintaining an appropriate quantity of parts storage. The large number of components that many businesses have to store in their inventories has a high financial expense. On either side, numerous companies and organizations lack the funding and resources necessary to supply this quantity of spare parts. Therefore, the issue is clear: higher inventories will lead to extra expenses, while on the contrary, a lack of stock will result in a disruption of the delivery of goods or services, and shortage costs would follow from this circumstance (Aronis et al., 2004). The topic's relevance has led to numerous research on spare parts inventories, all of which have attempted to manage maintenance and ordering procedures and stock levels. Identifying the ideal amount of components and optimum order quantity can significantly minimize overall investment in spare parts. Improving the reliability of the system, it moreover reduces system downtime and the associated expenses. In nearly all studies on this topic, the creation of models has focused on the condition of parts and systems. In these approaches, the state of the critical components is determined through observing systems and components or through scheduled assessments. Most of this research has modeled the components degradation process and produced maintenance and procurement forecasts based on this modeling. The MDP is one of the most utilized techniques. Several studies examined ordering and maintenance practices, whereas others cover either one of these topics. To overcome uncertainties and determine the appropriate amount of inventory, we aim to provide an approach that extends earlier research from a unique perspective and aspect. One of the key objectives of this viewpoint is to avoid over-storing spare components and to have them available when needed. The inventory level can be established in the interim by analyzing the system's present and potential subsequent states. By concentrating on the available data regarding the inventory system's condition, we attempt to develop an estimation of the demand for critical components over various periods in this research. The present study focuses on the system state information acquired for such an objective to forecast the demand for spare parts accurately. This study does not address maintenance practices; instead, it concentrates primarily on providing a decision approach to assist with finding the demand for spare parts. The study's methodology can be applied to any situation with enough online or historical data to help find the inventory system state. This research aims to give a flexible, functional, and reliable method using the power of data. In order to control crucial spare parts, research was done utilizing the ANFIS and MDP. This study aims to establish the ideal state of inventory control for vital parts.

The rest of this research is structured as follows. Following this introduction, section 2 describes the problem briefly but comprehensively. Section 3 examines the relevant literature on the topic under discussion. We propose our approach in section 4. Section 5 includes the result and discussion on the developed method and a case study. Lastly, the conclusions are presented in Section 6.

II. PROBLEM DESCRIPTION

This research presents a model to predict the inventory system's behavior based on past periods' data. This behavior is explained by four states, each representing a demand for spare parts. This model considers a single identical critical component in a group of similar machines. We do not monitor the degradation rate of installed components. If this component fails during the period, it is considered non-repairable and should be replaced with a new one. In the case of component failure, replacement is done quickly, and the machine continues to work normally, so we do not consider a preventive replacement. The component's failure rate depends on the machines' operation hours, but other factors in the working environment can also be considered. The machine breakdowns follow an irregular pattern, and the need for spare parts in each period can differ. Therefore, the demand for spare parts in each period is intermittent. In the case of an inventory shortage, machine breakdown will lead to prolonged operation disruption and financial loss, and high inventory levels for spare parts will contribute to additional storage costs. In this situation, our model aims to determine the demand and help make decisions about optimal inventory levels for upcoming periods. To this end, each period will be assigned to a state. Four states are established that can be found in section 4.2.

Our model processes available data from the operation line and inventory system using machine learning algorithms and, after discovering patterns and knowledge (Kamranrad et al., 2021), then transfer this knowledge to MDP. MDP is responsible for simulating and predicting the state of the inventory system for the subsequent periods. Being in each of these states will determine the demand and generally the conditions of the inventory system. By being aware of the state, it will be possible to decide on the optimal spare parts order. Notably, data can include any information that affects the operation of the installed component. The more information and the bigger the data, the more accurate the model will be. The model can utilize online or historical data to work. However, in this study, we used historical data from previous periods to predict the state of the inventory system for the following periods.

How can machine learning help? Keizer et al. (2011) found that considering the information of the entire system can help reduce costs significantly. Therefore, the machine learning process can be suitable for this purpose because it can handle complex data with numerous features, extract the system's behavioral characteristics, and provide them to the Markov chain to predict the following states.

Why do we use the ANFIS model? ANFIS is a complex model that can handle large data with many features. So this paves the way to use the model in many fields (Bonab, 2022).

The reason for the superiority of state-oriented politics: According to Lin et al. (2017), the state-dependent optimal policy causes a significant cost reduction compared to the state-independent policy.

The reason for using the Markov model: Markov process, because of its efficiency in predicting the condition of components or system's behavior, is used as a forecasting method. Previous works have used the Markov chain to model the degradation process of an installed part to predict the state of that component for maintenance or replacement. In this article, because the degradation of the component is not considered, we used the Markov process to determine the next state of the inventory system according to the system's current state.

III. LITERATURE REVIEW

In different studies, various techniques have been used to employ condition-based approaches. These studies also addressed various objectives and perspectives. We put up Table I to conduct a thorough and efficient evaluation of the literature to evaluate the studies on condition-based parts management.

Table I. Studies on condition-based methods

References	***Considered conditions***			***Considered policies***			***Methods used***
	Installed components	***System***	***Inventory***	***Maintenance***	***Replacement***	***Inventory***	
Smidt-Destombes et al (2004)	■			■		■	They provide a k-out-of-N system with identical, repairable components.
Ghodrati and Kumar (2005)	■				■	■	Modeling covariates in the regression analysis, step down procedure.
Chakravarthy (2006)	■			■		■	They outline a k-out-of-N reliability system and study that as a continuous time Markov chain.
Elwanay and Gebraeel (2007)	■				■	■	A sensor-based decision-making model.

Ilgin. and Tunali (2007)	■			■		■	Using genetic algorithms, they offer a simulation approach to optimize spare provisioning and preventive maintenance (PM) practices.
Wang et al. (2009)	■			■	■	■	They create a model for a Monte Carlo simulation and a simulation model for the system's functioning based on the established condition-based replacement and spare provisioning policies.
Lanza et al. (2009)							They propose an approach for figuring out when to perform preventive maintenance and when to stock up on spare parts. A stochastic optimization approach is used to accomplish this goal in accordance with a dependability model.
Tinga (2010)		■		■			Usage-based maintenance (UBM). Load-based maintenance (LBM).
Rausch and Liao (2010)	■			■	Production	■	A framework was established that includes condition-based maintenance and production and spare part stock management.
Louit et al. (2011)	■			■		■	Reliability-centered maintenance (RCM) terminology and remaining useful life of a component.
Li and Ryan (2011)	■					■	They model the degradation procedure using the Wiener process. Updates to monitored conditions are made using a Bayesian process.
Neves et al. (2011)		■		■			Hidden Markov Model theory.
Keizer et al. (2011)	■	■		■		■	They formulate their model as a Markov Decision Process.
Wang and Syntetos (2011)	■			■	Spares demand forecast		They make an effort to connect predictions to presented maintenance policies.
Frazzon et al. (2011)					Demand forecast	■	They provide a sensitivity analysis based on simulation and mathematical programming.
Giorgio (2011)	■						They provide a Markov chain degradation model.

Tracht et al. (2013)		■			Failure prediction	Spares demand forecast	Data mining, a binomial distribution, and the proportional hazards model (PHM).
Boudhar et al. (2013)	■				■		They offer a replacement order/remanufacturing strategy and want to assess the quality of new components before using them. Also, they provide a solution based on a genetic algorithm and mathematical modeling of the issue.
Wang et al. (2013)	■				■	■	They model the part's degrading trend using the Wiener process. Real-time CM data are used to adjust parameters using the Bayesian approach and the expectation maximization (E.M.) algorithm.
Panagiotidou (2013)	■			■		■	Ordering of spare parts and maintenance strategies were examined concurrently in a system with several components.
Hellingrath and Cordes (2014)		■		Estimating spare parts demand	Spares supply chain planning	Breakdown forecasts	They incorporate prediction methods with the condition monitoring data provided by IMS.
Wang et al. (2015)	■			■		■	They provide a methodology for integrated decision-making for spare parts and equipment maintenance.
Kareem and Lawal (2015)	■				Spare parts Failure prediction		Through the use of ABC analysis, they provide a system that dynamically determines essential equipment and spare parts and offers a model for forecasting the failure of spare parts in the automotive sector under extreme circumstances.
Hu et al. (2015)	■			■	Spare parts demand forecast		They forecast the need for spare parts using a two-dimensional preventive maintenance strategy that considers the components' installation and operating times. The mathematical model has also been solved using a different approach.
Cheng et al. (2016)		■		■	■		They consider a production inventory system in which the quality is associated with the degree of deterioration and subsequently offer condition-

							based maintenance and replacement plans for the system. The gamma process is used to model how a production system degrades.
Wang et al. (2016)	■			■		■	They provide a decision-making approach for a single component system that is exposed to stochastic and ongoing degradation under a condition-based maintenance strategy.
Saalmann et al. (2016)	■		machine	Failure forecasting	Machine control	SPSC planning	They deal with the integration issue of IMS (intelligent maintenance systems) devices and supply chains for spare parts (SPSC).
Lin et al. (2017)	■	■				■	They use a discrete-time Markov decision process to model this issue (MDP). Compared to a state-independent stock policy, a state-dependent approach saves 20% more cost.
Bousdekis et al. (2017)		■		■		■	They provide a proactive event-centered decision-making approach to optimize the spare parts inventory and preventive maintenance.
Cai et al. (2017)	■			■		■	They present a spare parts appointment policy based on forecasting the remaining useful life. Also, they provide an optimization technique that considers spare parts inventory and preventive maintenance.
Liu et al. (2017)		■		■	■		They provide a maintenance strategy for a deteriorating system and consider operational costs connected to its age and condition. As the system ages and the degree of degradation rises, the costs also rise. The Wiener process with linear drift is a characteristic of the degradation process.
Eruguz et al. (2017)	■				■	■	They address the combined maintenance and spare part optimization challenge for a single moving asset's critical component and model the problem using a Markov decision process.

Bülbül et al. (2019)					■	■	They involve the joint challenge of managing spare parts inventories and preventive replacement. They provide a precise dynamic programming formulation to reduce the total estimated cost over a limited planning horizon.
Wang and Zhu (2021)	■	■		■		■	They utilize the gamma and the Wiener process to simulate the deterioration of components. They offer an algorithm for optimizing the CBRICP for the k-out-of-n:F system using MDP and dynamic programming.
Aliunir et al. (2020)				■		■	A preventative maintenance and spare parts stock integration approach is suggested.
Muniz et al. (2020)	Maximizes the total criticality of spare part items					■	To address spare parts inventory control during the initial provisioning phase in the mining industry, they provide a new hybrid approach based on criticality analysis and optimization.
Usanov et al. (2020)	■			■		■	They combine dynamic spare parts control with condition-based maintenance in a network setting. They design the issue as a Markov decision process and include the degradation process in the model.
Farsi and Zio (2020)	■			■		■	In order to obtain the lowest cost and highest availability, a joint optimization strategy based on GA-PS and Monte Carlo simulation is suggested. Additionally, the impact of spare parts degradation in storage is considered when assessing system performance.
Dendauw et al. (2021)	■			■	■	■	They suggest a critical level strategy that is dependent on conditions. They perform Preventive maintenance under this strategy so spare parts can be used even when the inventory level is over the critical threshold.
Kang et al. (2021)	■			■			They provide a cutting-edge machine learning-based method for automating the equipment

							failure prediction process in continuous manufacturing lines.
Zhang et al. (2021)	■			■			They create a model-based reinforcement learning strategy for maintenance optimization. Over a limited planning horizon, the presented technique identifies maintenance activities for each level of degradation at each inspection time.
Tusar and Sarkar (2022)	A critical review and comparative study						The study looked at well-known spare parts models in Offshore Wind Farm, presented the findings methodically, compared them to some essential determining criteria, conducted a critical analysis, and analyzed the models' relevance.
Present study		■	■		■	■	We offer a Neuro-Fuzzy Inference System for condition information training and a Markov Decision Process for recognizing the following states of the system as a decision-making tool in determining demand and optimal levels of spare parts.

Ordering, inventory, repair, operational rules, and maintenance have all been explored in the publications on this topic. Some studies look at just one of these, whereas others address more. In this respect, several studies have concurrently accompanied inventory management and maintenance strategies, such as Wang and Zhu's (2020) dealing with spare parts from the viewpoint of inventory control and maintenance. They conclude that recharging spare parts in the stock point depends on maintenance strategies and the system's state. They discuss the best approach for managing inventories of non-repairable components and replenishing them under various system conditions. When making decisions, the installed components' condition is considered in addition to the system's state. In order to achieve this, the Wiener and Gamma process is used to predict the state of degradation of installed components. The quantity of degrading parts is also considered while determining the best maintenance and inventory strategy. They optimize the CBRICP for a k-out-of-n: F system using the MDP in conjunction with dynamic programming. Additionally, Keizer et al. (2011) take into account these two policies. They suggest that while employing degradation criteria for a system with a single part can be beneficial, doing so for a system with multiple components may not always be the best option. They thus offer an optimization strategy for a system with multiple parts, including a condition-based spare parts inventory and condition-based maintenance (CBM). They find out that considering the whole system information rather than using a more standardized inventory policy, such as (s, S), further reduces costs. Bousdekis et al. (2017) offer a proactive event-driven decision approach for spare parts inventory and optimizing maintenance strategies in this field. After putting the developed framework into the trial, they discovered that maintenance and inventory costs significantly decreased by switching from a time-based strategy to a CBM approach. To prevent a large amount of stock and a lack of replacement components, Cai et al. (2017) study inventory and maintenance concurrently. They present a hybrid optimization method of spare parts inventory and preventive maintenance (Rastgar et al., 2021) after first recommending a spare parts appointment policy based on the prediction of residual functional life.

Additionally, Smidt-Destombes et al. (2004) seek to establish a fair relationship between a k-out-of-repair System's capacity, component inventory, and preventative maintenance strategy. The maintenance starts whenever malfunctioning components' numbers reach a predetermined critical threshold. The spare parts are then used to replace these components. After that, damaged components are fixed at a repair facility. The spare parts inventory policy, repair capacity, and maintenance are additional factors that affect how well the system operates, and the authors try to balance these three factors.

The Markov process is frequently employed in state-dependent studies, particularly when simulating the deterioration process. The Markov process is used by Lin et al. (2017) to design the process of component deterioration. They consider the state of a single critical component in a group of machines. Based on a finite state space Markov chain mechanism, this crucial part deteriorates over time. It is also expected that each period can only have one state transition. As a result, the component can only experience its final stage of degradation before failing. At the start of each period, the degradation state of the components is carefully examined. A functional part from the stock is used to replace the failed part. If spare parts are unavailable when needed, there will be an immediate fee associated with obtaining them from some other sources. They use a discrete-time MDP to describe this issue and suggest three heuristic approaches to streamline computation. They discovered that compared to the state-independent stock policy, the optimal policy reduces costs by 20%. It should be emphasized that in this approach, maintenance policies were not taken into account. Moreover, according to Giorgio (2011), the components' age and condition during the slow decline can have an impact. As a result, they offer a four-parameter Markov chain model whose transition matrix depends on the component's present age and condition. The reliability function and the average remaining life are predicted based on the component's age, present state, and deterioration progress throughout upcoming time intervals. Another research adopted the Markov process to represent system conditions rather than components deterioration; Neves et al. (2011) seek to offer an algorithm for the optimum CBM policymaking. Their primary contribution is creating an optimization method and a methodology for identifying the model's input parameters. They address this problem in their model, noting that often CBM approaches do not go into detail about the model's input parameters. They offer theoretical and real-world problems and investigate a system with periodical monitoring, and a discrete-time Markov process shows the system's status. They employ a hidden Markov model and conclude that a method that incorporates optimization and model parameter calculation from historical data is the key achievement of their model.

Some studies use various methodologies in place of the Markov process to represent the deterioration process of parts. Li and Ryan (2011) build a model for incorporating real-time state monitoring data into stock management for spare parts. The Wiener process is used to model the component's degradation process, which is monitored by the state monitoring process. The life distribution of the working part was then created using the established model to calculate the demand distribution for spare components. This estimation is updated periodically in a Bayesian pattern by gathering data on deteriorating components. Wang et al. (2015) also address the part's deterioration as a continual gamma process with constant status monitoring. Due to the degradation phases' uncertainty, Wang et al. (2009) suggest condition-based reliability to typify different and uncertain degradation stages whenever a component malfunction occurs. Elwanay and Gebraeel (2007) also offer a deterioration modeling approach for calculating the residual life distribution of partly deteriorated parts. Some studies in the field of spare parts concentrate mainly on maintenance procedures. Wang et al. (2015) aim to improve spare parts procurement and equipment maintenance procedures. They consider a single-equipment system with randomized and continual deterioration rates for a state-dependent maintenance decision process. To start, they put up a probability model for figuring out the ideal stockpile amount of spare parts to satisfy the need for a predetermined stockout likelihood. The replacement decision of the equipment and ordering components was then made collaboratively, relying on the degree of deterioration and the cost of operation to optimize the policies taken into consideration. In further research by Rausch and Liao (2010), CBM is used to manage the inventory management techniques for both production and spare parts. On a critical part of manufacturing machinery, they apply this technique. Their approach is founded on observing the desired components' deterioration process. They give a valuable tool to maintain deteriorating parts efficiently. They declare that the overall manufacturing cost will be greatly decreased by putting the proposed stock management and production model into practice.

According to Tinga (2010), preventive maintenance is a crucial step to preserving system uptime. He emphasizes maintenance policies. Rather than corrective approaches, they consider preventive maintenance practices. As they suggest, the full-service lifespan of parts is used in corrective approaches; thus, unexpected breakdowns, operation disruptions, and damages to several other components are to be anticipated. They offer two brand-new ideas that combine static maintenance with condition-based maintenance: usage-based maintenance and load-based maintenance. This approach involves monitoring usage or load parameters to evaluate the system's state.

Due to several scholars, the subject of reliability has not received enough attention. In this context, Ghodrati and Kumar (2005) think that many studies emphasize accessibility and inventory control. They contend that these investigations fail to address how the operational environment factor that can affect reliability. They argue that the operating environment and time affect a system's reliability. Therefore, the predictions cannot be reliable enough without considering these factors. Additionally, Frazzon et al. (2014) use intelligent maintenance platforms to profit from technical condition data to increase the accuracy of spare parts demand forecasts. The suggested approach utilizes simulation-based sensitivity analysis and mathematical programming. A state-dependent replacement, reliability, and spare parts provisioning strategy is also put forth by Wang et al. (2009). They create a simulation model to reduce cost rates and employ a genetic algorithm to optimize decision factors. They employ suggested principles from a case study to optimize the maintenance plan to achieve this goal.

This topic at hand, like other studies in various fields, has made use of prediction, as Tracht et al. (2013) propose an enhanced forecasting framework that involves SCADA data from a wind farm, data mining, and the proportional hazards approach, and binomial distribution. As a result, they can foresee the demand for components and reliably estimate failure likelihood. Hellingrath and Cordes's (2014) primary objective is to develop a way of integrating state monitoring information and prediction techniques to estimate spare parts demand; therefore, they may effectively strategize the supply chain for spares. A method for making decisions about ordering spare parts was presented by Louit et al. in 2011, where a monitoring system is used to control the functioning components. As a result, their ordering decisions are based on the components' anticipated remaining service life. The component's age and state of health are evaluated for this aim. They argue that if they can predict when the failing process would begin at the right time, the anticipated lead-time for receiving the part on-site will be shorter than that lead-time, negating the need to store the component.

Improving the correctness of decisions on replacements and spare parts stock is the topic of some studies. For example, Elwanay and Gebraeel (2007) argue that most approaches concentrate on developing decision policies based on population-specific reliability characteristics such as breakdown time distributions. These distributions cannot differentiate between the degradation traits of various components of the population because they are impacted by all of the population's deterioration procedures. Due to this, failure predictions will be less accurate, which will lead to less precise maintenance and stock decisions. They offer a sensor-based decision framework for components replacement and spare parts inventory to overcome this. They concentrate on a single-unit inventory and replacement approach, which computes the optimum spares ordering and ideal component replacement using the life distribution.

As discussed in the literature, our study follows a state-dependent approach. Our research considers the overall inventory system's condition rather than just one component's state. Most studies in the literature review benefit from statistical methods and mathematical modeling. In contrast, we describe a strategy focusing on machine learning and the MDP. In this regard, four states are established based on a unique method to study and categorize the system's behavior. In each period, the system can be in just one of these states, and in other periods, the system's behavior can alternate between these four states. Additionally, for each period, historical data is gathered for three variables: the quantity of failed spare parts, average inventory, and operating hours. Then the inventory system's state for each period is calculated based on these three variables using the proposed method in section 4.2. The ANFIS model is responsible for identifying patterns and knowledge hidden in data. Hereafter, the system's following states are determined by the Markov decision process. As a result, upcoming states reveal the demand and behavior of the inventory system so decisions can be made regarding the level of spare parts.

The most important innovation of our research is bringing the subject of state-dependent management of spare parts into machine learning and connecting that to the Markov process. Based on Kezer et al. (2011), the positive effect of including the information of the whole system is reducing inventory costs, and considering the importance of data in today's world, providing a machine learning-based approach for state-dependent problems seemed very necessary. Furthermore, unlike most condition-based methods, the degradation process of the desired component has not been directly monitored in this research. A set of variables connected with or affecting parts failure has been considered, like operation hours. The remaining useful life of the component is not included in the data. Instead, we tried to provide another way to categorize the inventory state of spare parts by relating it to a series of operational data, the average inventory, and the number of failures in each period. Since we use the machine learning approach, the number of these variables can increase, and there is no particular limit in this regard; this is one of the strengths of this model. Also, according to Ghodrati and Kumar (2005), considering operational environment factors that can affect the reliability of the systems can increase the reliability of predictions. Due to that, the machine learning algorithms have the ability to consider numerous environmental factors and discover knowledge and patterns which will end in increased prediction accuracy.

IV. RESEARCH METHOD

Given the problem's significance, in this research, by providing a framework, an effort has been made to identify the system state and, based on that, the spare parts demand for the following periods. A hybrid methodology of ANFIS and MDP is employed to build the model. The ANFIS model thus establishes the system's present state in the first phase utilizing condition data relating to working hours, failures, and replacements. It should be highlighted that because fuzzy logic is included, ANFIS can account for current uncertainty. The transition matrix is constructed in the following steps. The MDP is then used to determine the system's subsequent state. We may manage critical spare parts well to prevent spare parts inventory costs, both in terms of shortages and high stock levels, by understanding the system's current state and forecasting its future state. The developed method's total effect is shown in Figure 1. Figure 2 also illustrates the thorough process of the model under discussion.

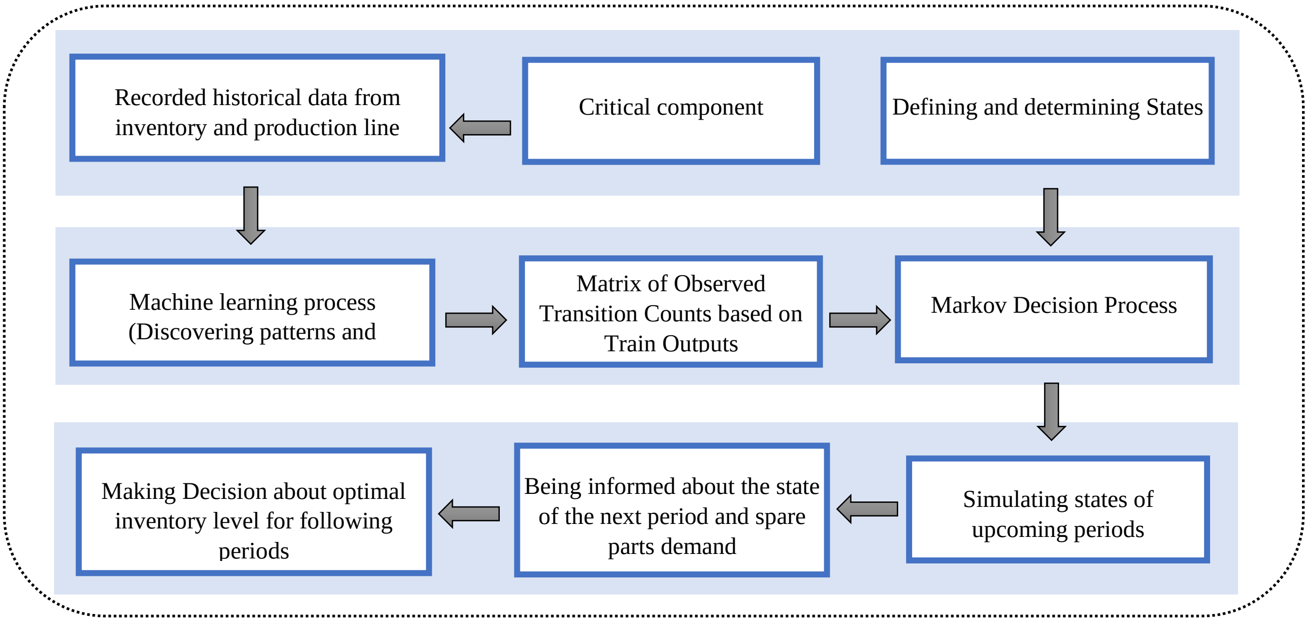

Fig 1. Overall view of the proposed model

A. Condition information

It is possible to determine the system's state or installed parts through sensor monitoring or routine assessments. Regarding the nature of the system under investigation, many different environmental and operational factors can be utilized to establish the system's condition. In the current study, some variables like operating hours, the number of failed components, initial inventory, ending inventory, average inventory throughout each period, and ordering data were considered to ascertain the system states. In other words, the model's primary goal is to determine the system's following states and behavior by utilizing several variables that can be used to draw an overview of the inventory system's future conditions. In order to achieve this, an identical critical component was taken into consideration, and data relating to it was collected throughout a number of periods. The ANFIS model will use these variables as input condition data.

B. State definition and determination

We establish four states to represent the inventory system condition. Each of these states reveals the inventory system condition at each period, which is indeed connected to the state variables that are taken into account. By establishing these four states, we hope to convey the reliability status of the inventory system at various points in time and classify the level of risk. Since the condition and reliability of the inventory system have a direct effect on the status and reliability of the operational system. The availability of spare parts can directly impact the operating system's reliability in the needed timeframe, which might result in significant issues. This approach of defining and identifying the states can be customized according to different systems and would be adjusted for any situation depending on the target system. The states have been determined using the creative technique described below:

In the first state, the system is in a safe condition if the number of component failures during the period is less than or equal to one-third of the average inventory. Shown as in Eq. 1:

$$\text{Number of failed spare parts} \leq \frac{1}{3} \text{Average Inventory} \tag{1}$$

Second state, if the number of failed parts during the period is more than one-third or less or equal to two-thirds of the average inventory. As shown in Eq. 2:

$$\frac{1}{3} \text{Average Inventory} < \text{Number of failed spare parts} \leq \frac{2}{3} \text{Average Inventory} \tag{2}$$

In the third state, if the number of failed components in each period is more than two-thirds or less than the average inventory, the system is in alarm mode. Determined as Eq. 3:

$$\frac{2}{3} \text{Average Inventory} < \text{Number of failed spare parts} < \text{Average Inventory} \tag{3}$$

In the fourth state, if the number of failed parts in each period is more than or equal to the average inventory, then the inventory system is in an unfavorable and very high-risk state. Determined as Eq. 4:

$$\text{Number of failed spare parts} \geq \text{Average Inventory} \tag{4}$$

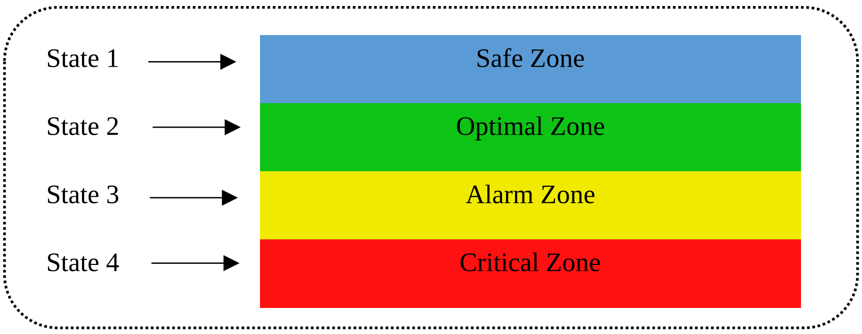

Fig 2. Color indication of states

The safe zone represents that there would be few breakdowns and the inventory system have more than enough stock to deal with the condition. The optimal zone means there would be some breakdowns and the inventory system has enough stock to deal with the situation. The alarm zone represents that the number of failures would rise, and consequently, the inventory system for spare parts would tackle a pretty demandable period. The critical zone means that the demand for spare parts would be high, and the spare parts inventory level would not be able to face this demand, so decision-makers should take action to tackle the condition.

Notably, ML considers inventory states, the number of failures, and working hours for each period and provides this information to the MDP. The provided inventory state space (1, 2, 3, 4) can be modified according to the case of implementation or even replaced with a new technic.

C. ANFIS model

After identifying the variables, we employ the recorded data as inputs for the ANFIS model. We also think of each period's system state as the ANFIS target. In other words, the state column is considered the target for ANFIS. In the created ANFIS model, we apply FCM clustering, which employs fuzzy c-means clustering to construct a FIS. The model performs at its best by figuring out the ideal number of clusters. In general, several tests are carried out to find the ANFIS model's parameters' ideal values. Additionally, the data were split into two sections for the training and testing processes, with 70% of the data taken into account for training and the remaining 30% for testing.

D. Transition matrix

It is required to find the transition matrix following running the ANFIS model and obtaining the output. The ANFIS model's training output, which reflects the probability of transitioning from one state to another different state, is used to compute and create the matrix of observed transition counts. This matrix will be used to create a Markov chain. Then the Markov chain will obtain a transition probability matrix, which indicates the probabilities of moving between states and will be used in random walk simulation.

E. Markov Decision Process (MDP)

MDP aims to discover the best strategy for decision-makers and is founded on the probability transition matrix. We utilize the transition state matrix obtained in the previous step to forecast the system's upcoming state. A discrete-time, finite-state, and time-homogeneous Markov chain were used to achieve this. This method allows for the prediction of system states up to multiple further steps, allowing for appropriate inventory decisions.

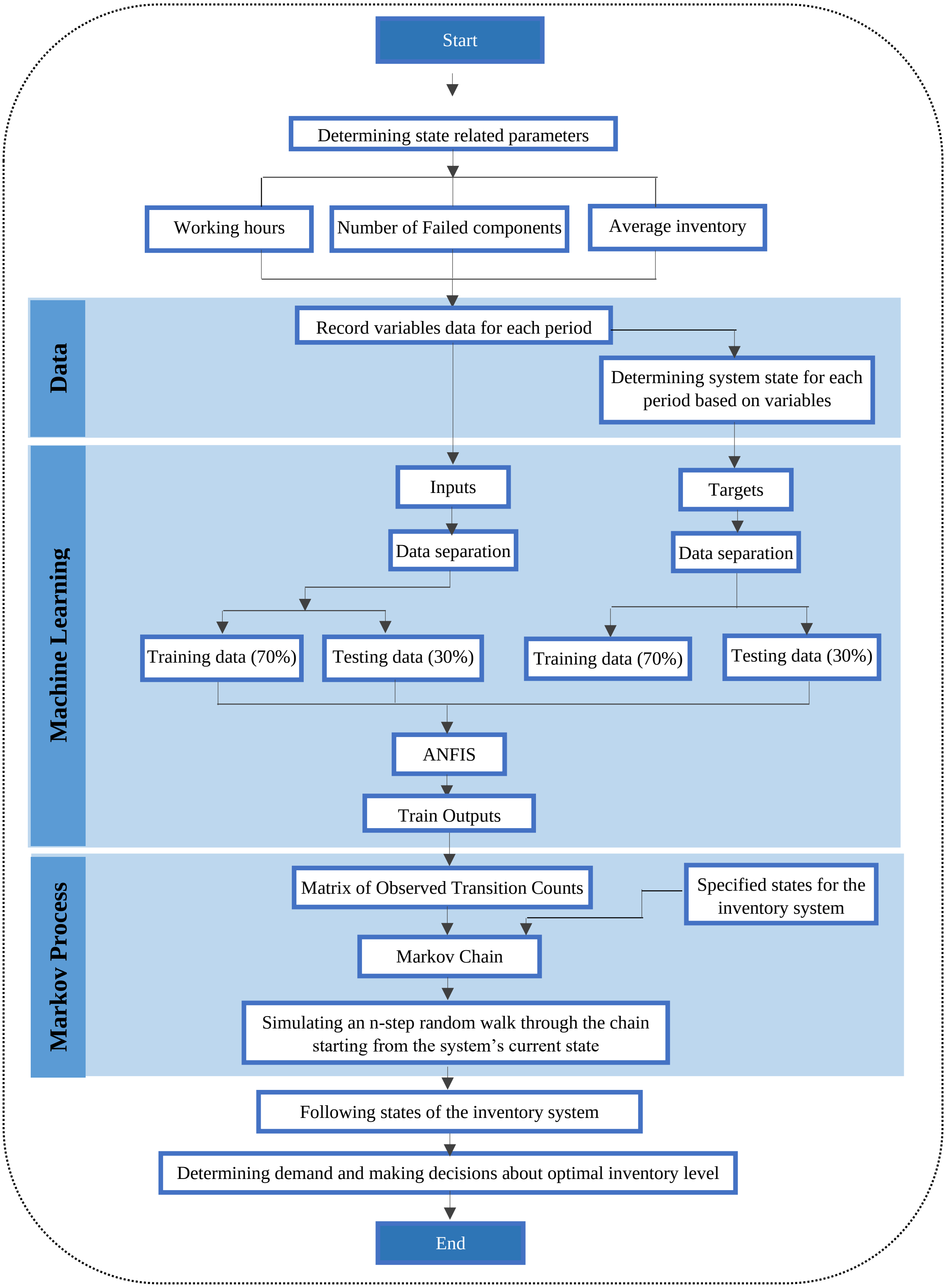

Fig 3. The detailed procedure of proposed model

V. RESULT AND DISCUSSION

Hellingrath and Cordes (2014) provide a forecasting procedure for spare parts demand. To this end, they gather condition information data provided by IMS and carry out demand forecasting based on a CBMF method. They argue that the most recent investigation on spare parts forecasting revealed a research gap in the integration of spare parts prediction models and condition monitoring data. Considering this problem, they aim to address the gap by providing a forecasting approach. Their study shows the impact of data in increasing forecasting accuracy. In continuation of the same issue, Kang et al. (2021) utilize data and Artificial Neural Networks to predict the remaining life of spare components. Zhang et al. (2021) use online degradation data at inspection times and a reinforcement learning approach for maintenance optimization. They show that their data-driven method can generate the CBM policy of the same quality as the policies whit an accurate degradation model. The present study tries to extend the use of data and machine learning approaches in forecasting the state of the inventory systems to determine the demand for spare parts in the following periods. In the first step, we use the recorded state data for each period (Table II) to feed it to the machine learning model, and here the ANFIS model was utilized to process and train data.

Table II. Recorded state data

Training Data				***Testing Data***			
Inputs			***Targets***	***Inputs***			***Targets***
Working Hours	***Failed components***	***Average inventory***	***System state***	***Working Hours***	***Failed components***	***Average inventory***	***System state***
513	6	5	4	486	6	9	2
480	7	8.5	3	503	6	13	2
440	6	12	2	555	7	6.5	4
320	4	17	1	478	6	8	3
440	6	12	2	446	5	12.5	2
600	9	4.5	4	.			
570	7	6.5	4	. .			
612	9	8.5	4	385	4	12	1
623	9	7.5	4	460	5	12.5	2
532	6	9	2	488	6	7	3
. . .							
395	4	15	1				
439	4	11	2				
514	6	12	2				
520	6	6	4				
565	7	9.5	3				
488	6	11	2				
510	6	5	4				

In table II, three variables, including working hours, failed components, and average inventory, are independent or feature variables, and system state is a dependent or response variable. Then dataset is separated into training and test data (Figure 3). We initially developed a Sugeno fuzzy inference system (FIS) employing FCM clustering with state data and the attributes specified in Table III to establish the ANFIS model. Figure 4 also shows the Gaussian membership functions of the input variables. Each input variable has a membership function and a rule for each fuzzy cluster when using FCM clustering. Each output variable has an output membership function for each fuzzy cluster.

Table III. FIS properties

Name	*Method*
Clustering Type	FCM Clustering
Fuzzy System Type	Sugeno
Input Membership Functions	gaussmf
Output Membership Functions	linear
And Method	prod
Or Method	probor
Implication Method	prod
Aggregation Method	sum
Defuzzification Method	wtaver
Inputs	[1×3 fisvar]
Outputs	[1×1 fisvar]
Rules	[1×5 fisrule]
Number of Clusters	5

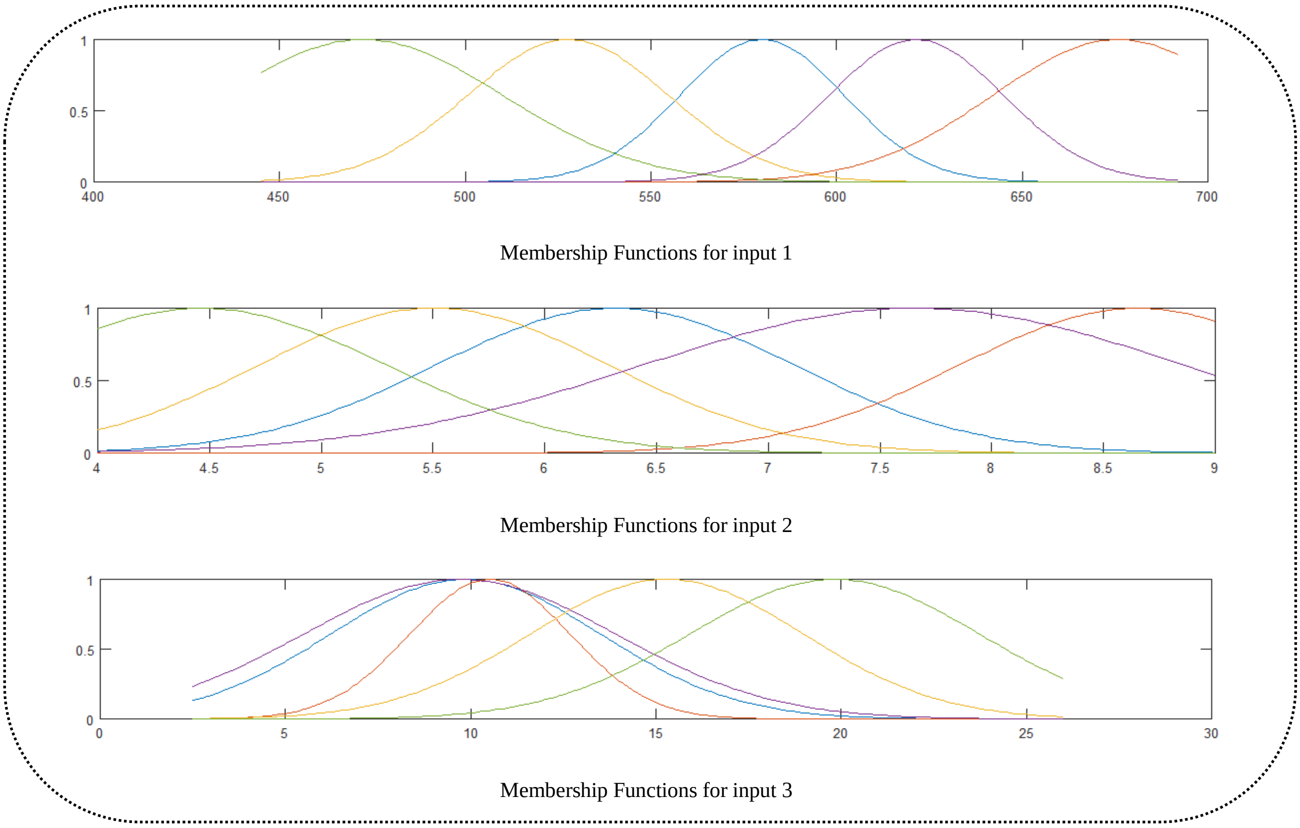

Fig 4. Membership functions for input data

The error goal was set to zero when the initial FIS was created to begin training the ANFIS. After several experimentations, epoch 2000 produced the best results, with ANFIS outputs closely matched to targets. For training data, ANFIS achieved an RMSE of 0.015511, and for test data, an RMSE of 0.73419. Additionally, a correlation coefficient was observed with training data R=0.99989 and test data R= 0.78639. Figure 5 shows a comparison of the Targets and Outputs of ANFIS. As a result, ANFIS was able to demonstrate acceptable performance. Table IV also provides the ANFIS features that were described.

Table IV. ANFIS info

ANFIS info	
Number of nodes	46
Number of linear parameters	20
Number of nonlinear parameters	30
Total number of parameters	50
Number of training data pairs	34
Number of checking data pairs	0
Number of fuzzy rules	5

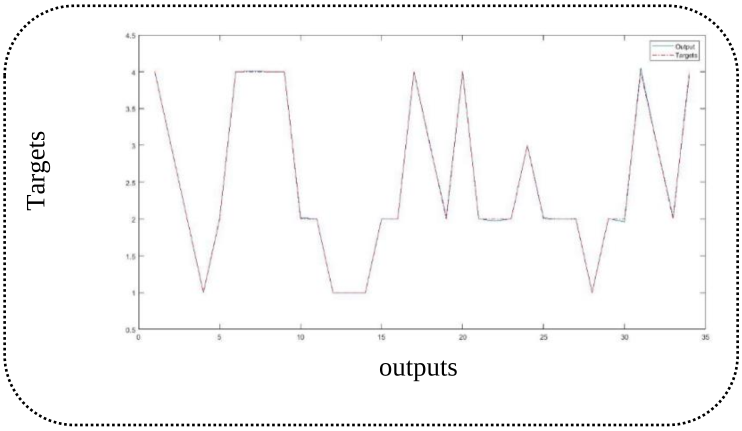

Fig 5. comparison between Targets and Outputs of the ANFIS

A transition matrix will be produced once the ANFIS model has been created and the training output has been received. In this case, the MATLAB function can be used to create a Markov chain using either a probability matrix or a matrix of observed transition counts. The present study uses a matrix of observed transition counts to develop the Markov chain. The transition probability matrix and the matrix of observed transition counts, accordingly, are illustrated in Figures 6 and 7.

	State 1	State 2	State 3	State 4
State 1	0.4	0.6	0	0
State 2	0.1875	0.4375	0.0625	0.3125
State 3	0	0.75	0.25	0
State 4	0	0.25	0.375	0.375

Fig 6. Transition probability matrix

	State 1	State 2	State 3	State 4
State 1	2	3	0	0
State 2	3	7	1	5
State 3	0	3	1	0
State 4	0	2	3	3

Fig 7. Matrix of observed transition counts

The developed Markov Chain features are shown in Table V. Figure 8 also illustrates the directed graph related to the developed Markov chain.

Table V. Markov Chain properties

Properties	
P	[4×4 double]
StateNames	["state 1" "state 2" "state 3" "state 4"]
NumStates	4

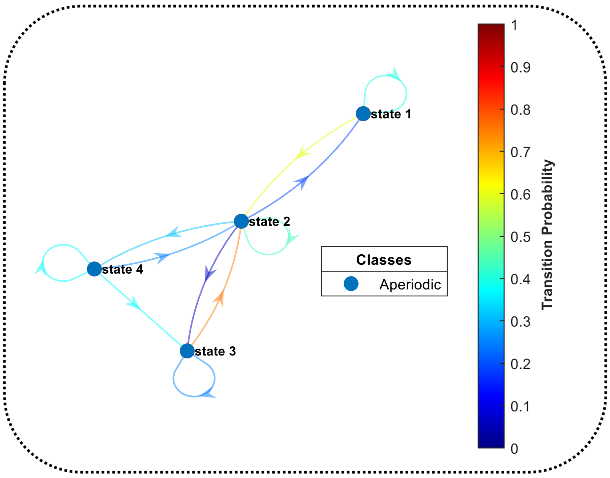

Fig 8. Directed graph of Markov chain

We can investigate the Markov chain's structure thanks to Figure 8. Therefore, all states fall within the category of aperiodic communicating class. Additionally, the edges of the graph are colored to represent the transition probabilities in P.

After setting up the Markov chain, we aim to simulate a ten-step random walk through the chain to see the states reached by simulation. The indices of the states reached during the random walk are contained in a ten-by-one vector X, where rows correspond to steps in the random walk. The realized starting state is in the first row. Because X(1) is 4, the random walk begins at state four. The initial state can be specified optionally, or the simulation will randomly start from a state. Position at step n + 1 is highly correlated with the position at step n. Therefore, we started a random walk from state four according to the system's last state. Figures 9 and 10 show the X and random walk, respectively. Figure 11 also depicts the path of a random walk through the states.

$$X=\begin{bmatrix}4\\4\\3\\2\\3\\2\\2\\3\\2\\3\end{bmatrix}$$

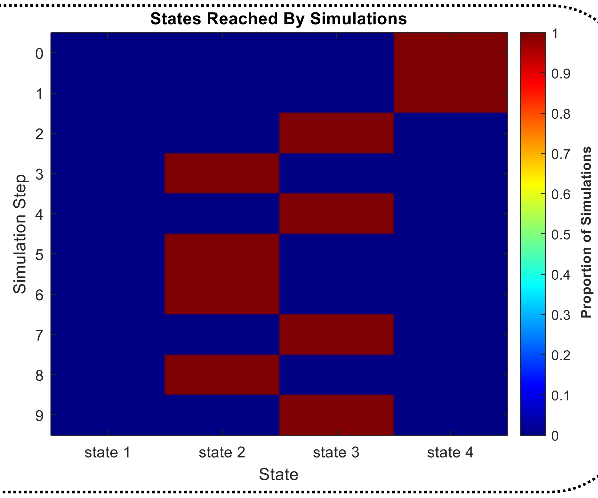

Fig 9. states visited during the random walk **Fig 10. A heatmap of the random walk**

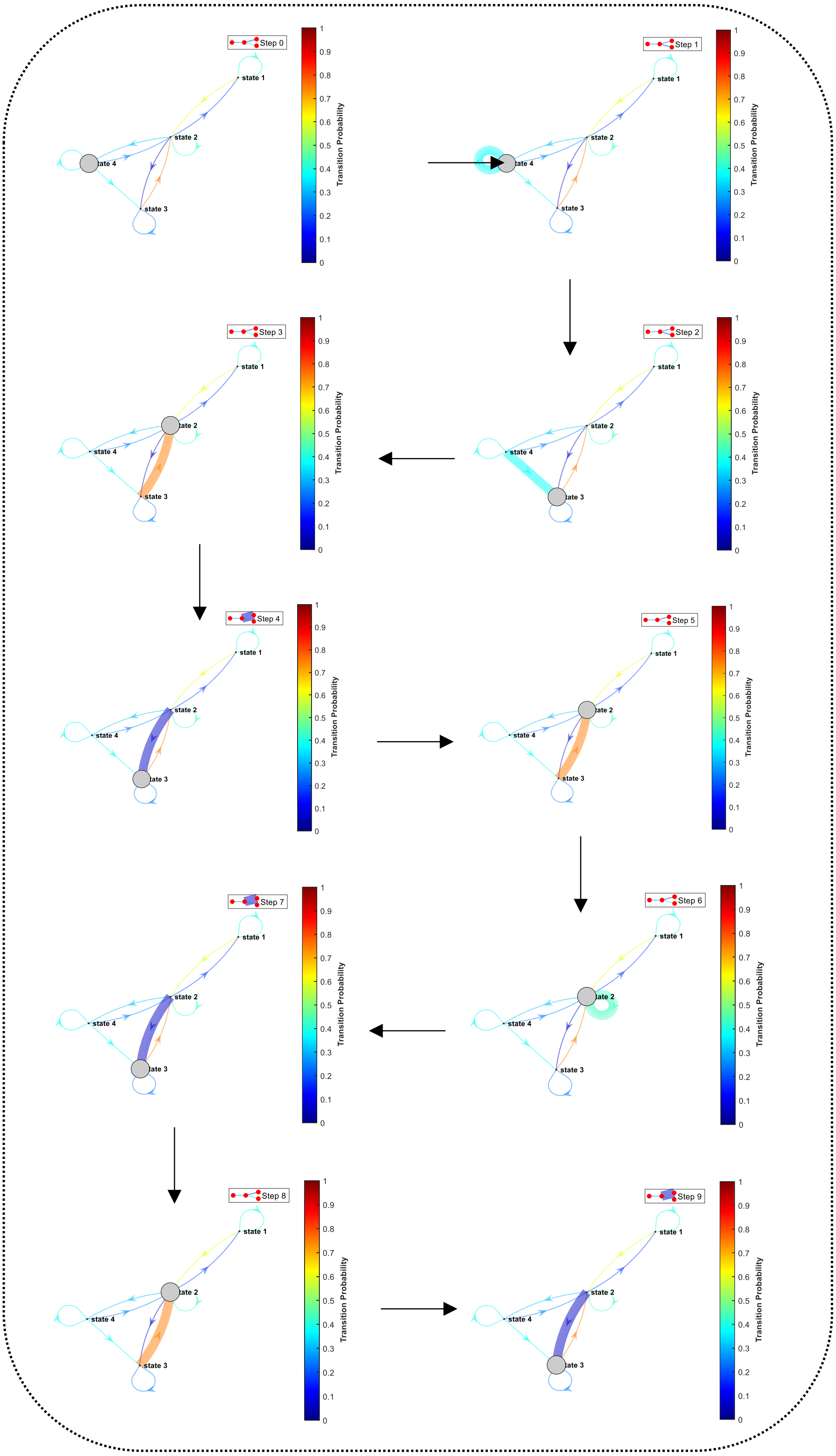

Fig 11. Illustrates the random walk path through states

A. The performance of the model

After simulating ten steps ahead, we intend to evaluate the model's performance and efficacy. A straightforward approach to see how well the forecasting method is performing is to create a confusion matrix. In other words, it is a brief table demonstrating how well our model predicts samples from different classes. Therefore, a confusion matrix was employed as a performance analysis tool. A confusion matrix can be created by addressing the Test target and simulated values (Chicco et al., 2021). This process determines how well the model fits values into their real classes. In essence, this tool compares actual values with those forecasted by the model. Figures 12 and 13 show the confusion matrix and the confusion matrix chart, respectively.

$$\begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 4 & 1 & 0 \\ 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 2 \end{bmatrix}$$

Fig 12. Confusion matrix

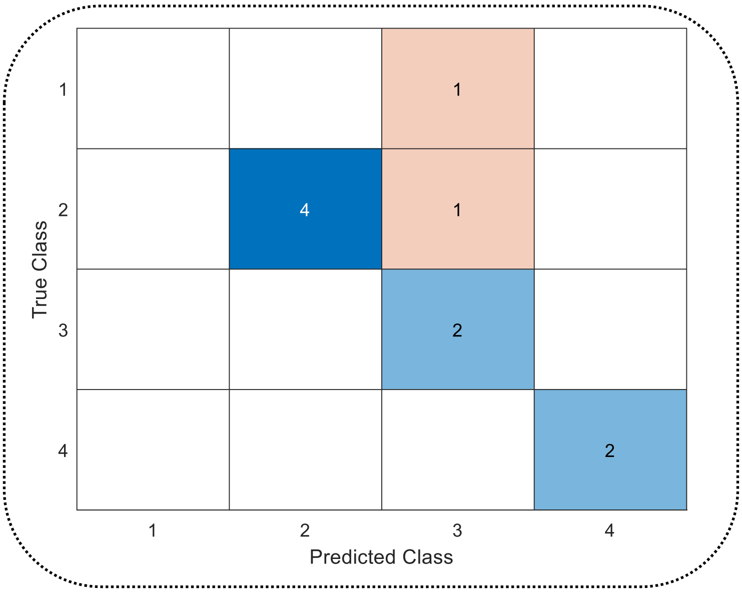

Fig 13. confusion matrix chart

Based on created confusion matrix, one data point which should be in group 1 was mistakenly placed in group 3. Four data points known to belong in group 2 are accurately categorized according to the confusion matrix, but one of the data points is incorrectly assigned to group 3. Also, the two data points in group 3 are classified appropriately. The data points, which should be in group 4, are correctly placed in group 4. This means independent random walks through the chain have accurately visited state two four times, two times visited state three, and two times state four. On the other side, random walk visited state three wrongly instead of state two and one-time state three instead of state one.

A. A. performance measures for the confusion matrix

An accuracy test can follow a confusion matrix analysis. It is preferable to employ this metric if we value each class equally. Equation 5 can be utilized to perform the accuracy test for this purpose. An accuracy value of 80% means that the identification of two of ten states is incorrect, and eight is correct.

$$accuracy = \frac{all\ the\ points\ that\ classified\ correctly}{all\ the\ points\ exist\ in\ confusion\ matrix} \tag{5}$$

So, the accuracy test can be calculated in percentage as follows:

$accuracy = \frac{2}{10} \times 100 = 80\%$

A.B. Other performance measures based on the confusion matrix

We utilized Python's Scikit-Learn to compute additional confusion matrix-related metrics; Scikit-Learn treats the rows as the true class and the columns as the predicted class. Table VI defines these measurements.

Table VI. Definition of performance measures of the confusion matrix

Sensitivity or Recall	The capability of a model to locate each and every pertinent point (state) in a set of data. It establishes that weather predictions were accurate (Olson and Delen, 2008; Saito and Rehmsmeier, 2015; Chicco and Jurman, 2020).
Precision	A classification model's capability to select just the pertinent data points. Precision describes the percentage of data points that the model claims were in the relevant class and were actually relevant (Olson and Delen, 2008; Saito and Rehmsmeier, 2015; Chicco and Jurman, 2020).
F1 score	The F1 score, which considers both measures, is the harmonic mean of precision and recall. The F1 score is attempted to be optimized in order to produce a classification model with the best possible recall and precision ratio. An F1 score can have a maximum value of 1.0. (Chicco and Jurman, 2020)
Support	Support is the number of class instances that actually occur in the dataset.

Figure 14 demonstrates the classification report of Python for the confusion matrix and shows values for performance measures and RMSE and MAPE error values.

```
Accuracy Score : 0.8
Classification Report :
              precision    recall  f1-score   support

           1       0.00      0.00      0.00         1
           2       1.00      0.80      0.89         5
           3       0.50      1.00      0.67         2
           4       1.00      1.00      1.00         2

    accuracy                           0.80        10
   macro avg       0.62      0.70      0.64        10
weighted avg       0.80      0.80      0.78        10

RMSE =  0.7071067811865476
MAPE =  30.0
```

Fig 14. Classification Report

In an ideal scenario, we would desire a model with precision and recall of 1. Achieving higher values of recall and precision is important. The F1 score allows combining the two metrics in situations where we wish to discover the best possible balance of precision and recall.

Here we aim to investigate these measures for each class. According to fig 14, class 2 represents that the Markov model was able to predict or walk through node two (state two) four times correctly out of five (support) or actual occurrences of state two in the test data set. Accordingly, the precision and sensitivity values for class 2 were 1 and 0.8, respectively. Also, class 3 shows that the model was able to walk through node three (state three) two times out of two (support) correctly whit precision and sensitivity values of 0.5 and 1, respectively. Class 4 demonstrates that the simulation was able to walk through node four (state four), two times equal to the actual occurrence for this class, and all measures for this class are 1. The model could not walk through state one and instead incorrectly predicted state three. Table VII represents all classes' Weighted-averaged precision, recall, and F1 score.

Table VII. Weighted-averaged measures

Weighted Precision	0.8
Weighted Recall	0.8
Weighted F1-score	0.78

Also, by evaluating the difference between actual and forecasted data, the efficiency of the model can be assessed according to the error with the lowest value. Root mean square error (RMSE) and mean absolute percentage error (MAPE) are the error measurement types used in this research. According to Table VIII, compared to the ARIMA model, the ANFIS+Markov model has the lowest value, with RMSE and MAPE values of 0.7071 and 30 percent, respectively (Zakaria et al., 2019). Table IX assesses the MAPE range (Lewis, 1982 & Kathiria and Arolkar, 2022).

Table VIII. Model comparison of forecast values.

Model	***RMSE***	***MAPE***
ANFIS + Markov	0.7071	30%
ARIMA	1.2459	48.2732%

Table IX. MAPE interpretation as per Lewis 1982 & Kathiria & Arolkar 2022.

MAPE	***Interpretation***
<10	Highly accurate forecasting
10–20	Good Forecasting
20–50	Reasonable forecasting
>50	Inaccurate forecasting

B. Interpreting system behavior and determining demand

In this part, we provided a sample and tried to put the suggested model into practice to predict the inventory system's upcoming states and behavior. We may decide on the proper spare parts inventory level now that we know the system behavior's direction. According to the proposed sample, the system has a propensity to transition to state 4 in the succeeding period. State four is a critical zone regarding spare parts demand and inventory. Based on the definition of states as specified in section 4.2, a critical zone means we will encounter a significant demand for spare parts, and the inventory system will not be able to tackle the situation in the upcoming periods if we do not take proper action. Moreover, when predictions for the following periods imply state four, we can consider this situation while planning and deciding the level of spare parts inventories for the subsequent periods.

The random walk started from state 4, the last state of the spare parts inventory system in the studied case, and predicted states 4, 3, and 2 as the following three states of the inventory system, respectively. By understanding that state four will be repeated for the next period, according to the fourth assumption in section 4.2, we can realize that the presented model has forecasted a critical condition for the next period, considering the current conditions of the system (Fig 15).

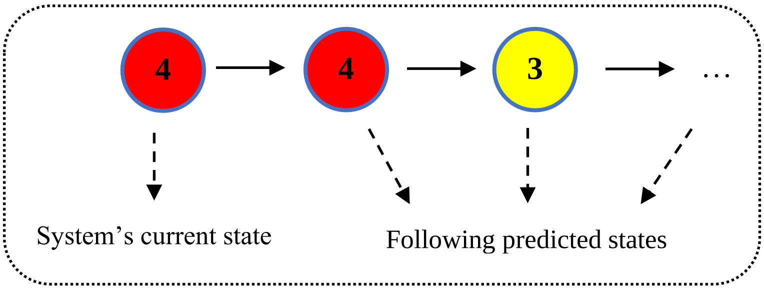

Fig 15. Classification Report

How do optimizing inventory levels relate to forecasting the state of the inventory system? Forecasting the inventory system's state is intimately connected to having optimum inventory levels. The historical data unveil the range of demand for spare parts in the past periods for each state. How much the model can predict the following states of the inventory system correctly, the accuracy of inventory estimate and optimization would be higher. Based on the available dataset, the failure rate of parts in each period was presented in Table X. According to table X, the maximum demand in state 4 is about nine. By considering the current period's ending inventory and the demand for the next period, a correct decision can be made about the balance of spare parts for the next period.

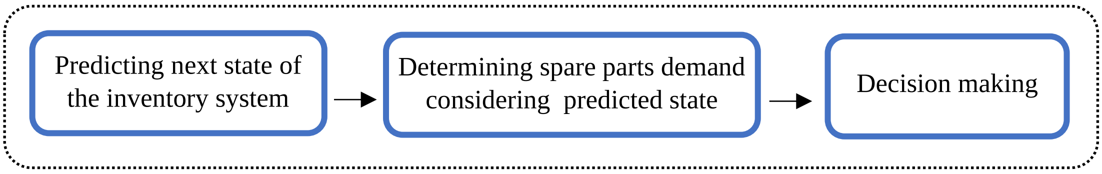

Fig 16. Classification Report

Table X. Model comparison of forecast values.

State	*Demand for spare parts*
1	3-4
2	4-6
3	6-7
4	6-9

C. Discussions and managerial insight

The results obtained in this study show that the presented model has an acceptable ability to predict the future states of the critical spare parts inventory control system. The developed model has more reliable results compared to comparable models, and that is because of its capability of random walk in transition matrix and memoryless property (Kathiria & Arolkar, 2022; Piccardi et al., 2017; Hazra et al., 2017; Tserenjigmid, 2019). In general, this paper plays a crucial role in linking state-dependent inventory control of spare parts to the world of machine learning. At the same time, thanks to machine learning algorithms, it can handle situations with many variables, factors, features, and big data, which can lead to more accurately predicting system states. Also, this study gives an overview of how to use data and improve condition-based predictions. The analysis results can be obtained smoothly, and it can be an appropriate and understandable tool for inventory control managers to make easy and optimal decisions.

VI. CONCLUSIONS

One of the most crucial parts of inventory control is managing spare parts, which is essential to keeping efficiency. There is unreliability in this situation because the need for spare parts is frequently sporadic. As a result, much study has been carried out to manage spare parts depending on the condition of components and systems. The development of predictive models with high accuracy is a suitable option for estimating the condition of installed parts and determining the state of the inventory system of these parts. It can significantly help spare parts management. In this regard, a hybrid model of the machine learning process and Markov chain was presented in this paper. ANFIS model is responsible for the machine learning process because it has a good ability to train large data with many variables and features. Next, to connect ANFIS to Markov, we needed a transition matrix. The transition matrix was created based on the output of ANFIS training and was used to create a Markov chain. We utilized a random walk to move along the Markov chain to simulate the following states. The current state of the inventory system should be considered the starting state because the current state is decisive in the Markov chain transition to other states.

The case study showed that the model could predict the system's future states with acceptable accuracy. The measures such as accuracy, precision, and recall, all with values of 0.8, were indicative of the model's ability. Also, the model's performance was compared with the ARIMA model and demonstrated better results in this case. The RMSE error values for the presented model (0.7) compared to ARIMA (1.27) were significantly lower. Also, the MAPE for the proposed model (30%) was much lower compared to 48.27% for the ARIMA model.

Management insights can be summarized in the following:

1- Since the inventory of spare parts plays a vital role in the maintenance and repair of machines, managers should be cautious in providing parts and predicting the lack of these parts.

2- Forecasting of spare parts should be done with multiple and efficient techniques, and the accuracy of these techniques should be measured, and the forecast with the least error should be selected, so according to the method used in this research, it is strongly recommended to production managers.

For future suggestions, the introduced model can be utilized as follow:

- In the presented model, using online data collected by sensors instead of historical data can provide the real-time state of the inventory system.
- Maintenance and repair policies can be implemented by shifting from determining the state of the inventory system to determining the state of components in operation.
- In the case study section, a single component was considered. Several components can be regarded, and the model's performance can be compared with a single component model.
- Since one of the proposed method's key characteristics is flexibility, it is possible to make improvements and adjustments to many aspects of it. For instance, a different approach to identifying states may be provided, or alternative machine learning techniques could be used.

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