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Adapted Markovian model to control reliability assessment in multiple AGV manufacturing system

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Abstract. This paper presents a Markovian model for Flexible Manufacturing Systems (FMSs). The model considers two features of automated flexible manufacturing systems equipped with the Automated Guided Vehicle (AGV), namely the reliability of machines and the reliability of AGVs in a multiple AGV jobshop manufacturing system. Performance measure is a critical factor used to judge the effectiveness of a manufacturing system. The studies in the literature did not compare Markovian and neural networks, especially in the reliability modeling of an advanced manufacturing system, considering AGVs. The current methods for modeling the reliability of a system involve determination of system state probabilities and transition states. Since the failure of the machines and AGVs could be considered in different states, a Markovian model is proposed for reliability assessment. Also, a neural network model is developed to point out the difference in the accuracy of the Markovian model in comparison with the neural network. The optimization objectives in the proposed model are maximizing the total reliability of machines in shops in the whole jobshop system and maximizing the total reliability of the AGVs. The multi-objective mathematical model is optimized using an analytic hierarchy process.

1. Introduction

Traditional manufacturing has relied on dedicated mass-production systems to achieve high production volumes at low costs. As living standards improve and the demands for new consumer goods rise, manufacturing flexibility gains prominence as a strategic tool for rapidly changing markets. Flexibility, however, cannot be properly incorporated in the decision-making process, if it is not well defined and measured in a quantitative manner. Flexibility in its most rudimentary sense is the ability of a manufacturing system to respond to changes and uncertainties associated with the production process [1-3]. A comprehensive classification of eight flexibility types was proposed in Browne et al. [4].

Flexible Manufacturing Systems (FMS) are crucial for modern manufacturing to enhance the productivity involved with high product proliferation [5]. As one of the critical components of the FMS, the flexible Material Handling System (MHS) plays a strategic role in the implementation of the FMS [6]. According to Tompkins et al. [7], about 20-50% of the total production cost is spent on material handling. This makes the subject of material handling increasingly important. In addition, all the complexity of manufacturing is passed on to the MHS. Therefore, the flexible MHS has been vital for improving the FMS, to fulfill the requirements of high product proliferation.

Automated Manufacturing Systems (AMS), which are equipped with several CNC machines and the AGV-based material handling system, are

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designed and implemented to gain the automation and efficiency of production. To make use of all features of AMS, the planning in the AMS decision-making process is critical, because the planning decision has influence on the subsequent decision processes such as scheduling, dispatching, etc. The planning in automated manufacturing systems can be characterized as being online and short-term natured to respond to frequently changing production order. Given a production order, manufacturing planning function is responsible to establish a plan by decomposing the production task into a set of subtasks. An analysis of AMS dealing with changing demand can be found in [8]. An extensive review of the loading problem for an FMS can be found in [9]. An early stochastic programming approach to address the short-term production planning for an FMS can be found in [10].

Automated Guided Vehicle System (AGVS) becomes popular in many industrial fields because of its flexibility, reliability, safety, and also its contribution to the increase of productivity and the improvement of housekeeping. But, the performance of a material handling system is significantly influenced by several operating policies. One of the important operating policies is the positioning strategy of the idle vehicles on the guide path [11,12].

In most manufacturing systems, decision making is worked out at several stages of design, planning and operation. The role of performance modeling is significant in advanced manufacturing systems from economic viewpoints. However, events such as machine breakdown, changes in part type and volume, tool replacement, raw material and other short interruptions are effective on the desired performance of a manufacturing system. This problem is critical due to its impacts on the capacity of the system [13]. Researches on the automated manufacturing systems imply that the machine failure is the major problem in analyzing system performance, in comparison with other factors like raw material, equipment, software and workers [14]. Therefore, reliability considerations should be taken into account for manufacturing system analysis. Researchers who studied this problem include [15-21].

Since manufacturing systems experience different failure states, considering these states in modeling a reliability problem is of importance. The best way for considering system states in modeling is to employ Markovian property. Reibman [22] stated that the problem in estimating the probability of failure in different states is vital for reliability computations.

The increasing demand for the reliability assessment in manufacturing systems, under several random parameters, has been investigated by several approaches facilitating the computations of probability estimations. According to the following brief literature review, studies to compare Markovian and neural networks are few; especially, modeling the reliability of an advanced manufacturing system, considering AGVs, is also rare.

2. Literature review

The improvement of safety in the process industries is related to the assessment and reduction of risk in a cost-effective manner. Kančev and Čepin [23] addressed the trade-off between risk and cost related to standby safety systems. An age-dependent unavailability model that integrated the effects of the Test and Maintenance (T&M) activities, as well as component ageing, was developed and represented the basis for calculating risk. The repair "same-as-new" process was considered regarding the T&M activities. Costs were expressed as a function of the selected risk measure. The time-averaged function of the selected risk measure was obtained from a probabilistic safety assessment, i.e. the fault tree analysis. This function was further extended with the inclusion of additional parameters related to T&M activities, as well as ageing parameters related to component ageing. In that sense, a new model of system unavailability, incorporating component ageing and T&M costs, was presented. The testing strategy was also addressed. Sequential and staggered testings were compared. The developed approach was applied on a standard safety system in nuclear power plant although the method was applicable to standby safety systems that were tested and maintained in other industries as well.

The problem of selecting a suitable maintenance policy for repairable systems and for a finite time period was presented by Marquez and Heguedas [24]. Since the late seventies, examples of models assessing corrective and preventive maintenance policies over an equipment life cycle have been existed in the literature. However, there are not too many contributions regarding real implementation of these models in the industry, considering realistic timeframes and for repairable systems. Modeling this problem normally requires the representation of different corrective and/or preventive actions that could take place at different moments, driving the equipment to different states with different hazard rates. An approach to pattern the system under finite periods of time has been the utilization of semi-Markovian probabilistic models, allowing later a maintenance policy optimization, using dynamic programming. These models are very flexible to represent a given system, but they are also complex and therefore very difficult to handle when the number of system possible states increases. Marquez and Heguedas [24] explored the trade-off between flexibility and complexity of these models, and presented a comparison in terms of model data requirements versus potential benefits obtained from the model.

In the Generalized Renewal Process (GRP) reliability analysis for repairable systems, the Monte Carlo (MC) simulation method, instead of numerical method, is often used to estimate the model parameters because of the complexity and the difficulty of developing a mathematically tractable probabilistic model. Wang and Yang [25] proposed a nonlinear programming approach to estimate the restoration factor for the Kijima type GRP model I, as well as the model II, based on the conditional Weibull distribution for repairable systems, using negative log-likelihood as an objective function, and adding inequality constraints to model parameters. The method minimized the negative log-likelihood directly, and avoided solving the complex system of equations. Three real and different types of field failure data sets with time truncation for NC (Numerical Control) machine tools were analyzed by the proposed numerical method. The sampling formulas of failure times for the GRP models I and II were derived, and the effectiveness of the proposed method was validated with the MC (Monte Carlo) simulation method.

Ke et al. [26] considered a multi-repairmen problem comprising of M operating machines with W warm standbys (spares). Both operating and warm standby machines were subject to failures. With a coverage probability c, a failed unit was immediately detected, and attended by one of R repairmen if available. If the failed unit was not detected with the probability 1-c, the system would have entered an unsafe state, and must have been cleared by a reboot action. The repairmen were also subject to failures which result in service (repair) interruptions. The failed repairman resumed service after a random period of time. In addition, the repair rate depended on the number of failed machines. The entire system was modeled as a finite-state Markov chain, and its steady state distribution was obtained by a recursive matrix approach. The major performance measures were evaluated based on this distribution. Under a cost structure, the authors proposed to use the Quasi-Newton method and probabilistic global search Lausanne method to search for the global optimal system parameters.

Nowadays, Voice over Internet Protocol (VoIP) has become an evolutionary technology in telecommunications. Hence it is very important to study and enhance its dependability attributes. An analytical dependability model for VoIP was proposed by Gupta and Dharmaraja [27]. The study was focused on analyzing the combined effects of resource degradation and security breaches on the Quality of Service (QoS) of VoIP, to enhance its overall dependability. As a preventive maintenance policy to prevent or postpone software failures, which cause resource degradation, software rejuvenation was adopted. The dependability model was analyzed using semi-Markov process, which captures the effects of non-Markovian nature of the time spent at various states of the system. The steady-state, as well as the time-dependent analysis of the dependability model, was previously presented.

Zhou et al. [28] presented a maintenance optimization method for a multi-state series-parallel system, considering economic dependence and state-dependent inspection intervals. The objective function considered in the paper was the average revenue per unit time calculated, based on the semi-regenerative theory and the Universal Generating Function (UGF). A new algorithm, using the stochastic ordering, was also developed in the paper to reduce the search space of maintenance strategies and to enhance the efficiency of optimization algorithms. A numerical simulation was presented in the study to evaluate the efficiency of the proposed maintenance strategy and optimization algorithms.

A reliability assessment for Hard Disk Drives (HDDs) is important yet difficult for manufacturers. Motivated by the fact that the particle accumulation in HDDs, which accounts for most HDD catastrophic failures, is contributed to the internal and external sources, a counting process with two arrival sources was proposed by Ye et al. [29] to model the particle cumulative process in HDDs. The model successfully explained the collapse of traditional ALT approaches for accelerated life test data. Parameter estimation and hypothesis tests for the model were developed and illustrated with real data from a HDD test. A simulation study was conducted to examine the accuracy of large sample normal approximations that were used to test the existence of the internal and external sources.

An R out of N repairable system consisting of N independent components is operating if at least R components are functioning. The system fails whenever the number of good components decreases from R to R-1. A failed component is sent to a repair facility having several repairmen. Lifetimes of working components are i.i.d random variables having an exponential distribution. Repair times are i.i.d random variables having a phase type distribution. Both cold and warm standby systems are considered. Barron et al. [30] presented an algorithm deriving recursively in the number of repairmen the generator of the Markov process. Then they derived formulas for the point availability, limiting availability, distribution of the down time and up time. Numerical examples were given for various repair time distributions. The numerical examples showed that the availability is not very sensitive to the repair time distribution, while the mean up time and the mean down time might be very sensitive to the repair time distributions.

According to the brief reviewed literature, studies to compare Markovian and neural networks are few.

Especially, modeling the reliability of an advanced manufacturing system, considering AGVs, is also rare.

3. Statement of the problem

Here, a jobshop manufacturing system having multiple AGVs for material handling purpose is considered. In each shop, several machines perform the part processing according to a process plan. To transfer the parts among different shops, AGVs are employed. The reliability of the whole manufacturing system is concerned with the reliability of machines in shops and the reliability of AGVs. The failure of the machines and AGVs could be considered in different states. The failure occurred for machines are:

- Amateur operator;
- Equipment deficiency;
- Inappropriate part specifications.

Also, the failures of AGVs are due to:

- Carrier overload;
- Guide path fracture.

Using the Markovian property, we can configure the transition diagram and the corresponding matrix. The result of the Markovian process is the failure probability for machines and AGVs. These probabilities are applied in reliability computations. For reliability, first we conceptualize different scenarios existing in the proposed manufacturing system. The shops are in parallel since the parts are disseminated through the system, according to the process plan. The sequence of machines in a shop may be important or not, i.e. the part processing in a shop should be performed sequentially on the machines, or the sequence is not important and parallel machining is possible. Therefore, two separate cases of series and parallel should be modeled. AGVs are in series, and if one AGV breaks down then the whole system should wait until the AGV is repaired or taken out of the system.

The aim of the decision maker is to maximize the performance of the whole system. To achieve the aim, two objectives, namely maximizing the total reliability of machines in shops in the whole jobshop system, and maximizing the total reliability of AGVs, should be investigated. Also, for the economic viewpoint of the system performance, the third objective is to minimize the total repair cost in the system. As a unit (machine or AGV) in the system is broken down, the repair should be performed on it to prepare it for functioning.

The aims of conducting this study are:

- √ Developing a reliability assessment methodology for AGV-based manufacturing systems;
- √ Analyzing and including fault sources in machine-AGV state modeling in manufacturing systems;
- √ Markovian modeling for reliability assessment of a machine-AGV manufacturing system;
- √ Comparing the Markovian reliability assessment with the neural network method.

3.1. Model with reliability

It is necessary to incorporate reliability into the model to ensure the level of service for each machine in each shop and the AGVs. For modeling reliability, the approach of Ball and Lin [31] is adopted and further extended.

The reliability is defined as the probability that the system works until time t. If a machine in a shop is broken down, it can be regarded as a failure. A desired level of reliability can be achieved by limiting the failure probabilities. This approach for handling reliability is called the method of chance constraints in the context of mathematical programming. The use of chance constraints in a vehicle routing problem was illustrated in Stewart and Golden [32]. Carbone [33] used chance constraints for selecting multiple facilities under normally distributed demands. The model minimized an upper bound on the total demand-weighted distance while ensuring that the constraint was satisfied with specified chance or probability. Shiode and Drezner [34] used a similar approach in a competitive location problem on a tree network.

It is assumed that the reliability of each machine type and the AGV are independently due to exponential processes. Also, J is the total types of machines, i.e. drilling machines, turning machines and bending machines (three machine types). We discuss the reliability-based model as follows:

$R_j(t)$: The probability that machine type jth works until time t,

$$R(t)_{system} = \begin{cases} \left(1-\prod_{j=1}^{J}(1-R_j(t))\right), & \text{when machines in each shop are in parallel case} \\ \left(\prod_{j=1}^{J} R_j(t)\right), & \text{when machines in each shop are in series case} \end{cases} \tag{1}$$

In our proposed problem, AGVs are series and the machine types in each shop may be in parallel or series cases, and the shops are parallel, i.e. a composite system is configured. Therefore, the reliability of the system is as follows:

$$\left(1-\prod_{j=1}^{J}(1-R_j(t))\right) \geq \alpha, \tag{2}$$

where α is the lower bound for a desirable reliability of the system until time t. As previously assumed, the reliability of each machine type and AGV are independently due to exponential distribution:

$$R_j(t) = e^{\frac{-t}{\theta_j}}, \tag{3}$$

where θ_j is the exponential parameter for machine type or AGV breakdown. Then,

$$\left(1 - \prod_{j=1}^{J}(1 - e^{\frac{-t}{\theta_j}})\right) \geq \alpha. \tag{4}$$

It is obvious that to obtain a higher level of reliability, more cost is incurred to the system. Hence, a cost function ($C_j(t)$) is defined to keep machine type jth reliable until time t. For the whole system, we have:

$$\sum_{j=1}^{J} C_j(t). \tag{5}$$

4. Mathematical formulation

In this section, we construct the proposed failure state diagrams and matrices for machines and AGVs, using the Markov system separately. A Markov system is a system that can be in one of the several (numbered) states, and can pass from one state to another by each time step, according to fixed probabilities. If a Markov system is in state i, there is a fixed probability, p_{ij}, of it going into state j the next time step, and p_{ij} is called a transition probability. A Markov system can be illustrated by means of a state transition diagram, which is a diagram showing all the states and transition probabilities. The entries in each row add up to 1.

First, we configure the machines' state diagram. As stated before, the machines may be broken down in three states, namely (a) amateur operator, (b) equipment deficiency and (c) inappropriate part specifications. Note that the states refer to the breakdown state causes, i.e. the machine is working or it is broken down due to the failure states such as amateur operator, equipment deficiency and inappropriate part specifications. In another word, since we are modeling the reliability of the system, considering different state changes, it is common in Markovian computations to monitor the state transition, while all are the causes of breakdown. The state transition diagram for machines is shown in Figure 1.

As a result, the corresponding transition matrix P_{ij} is,

$$P_{ij} = \begin{bmatrix} 1-\alpha-\varepsilon & \alpha & \varepsilon \\ \beta & 1-\beta-\gamma & \gamma \\ \nu & \delta & 1-\delta-\nu \end{bmatrix}, \tag{6}$$

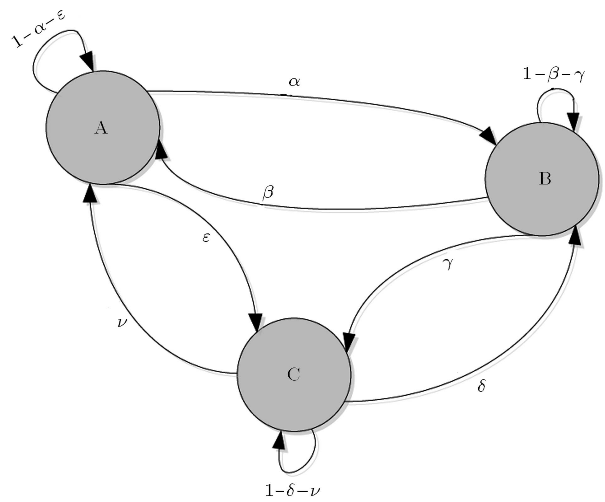

Figure 1. The state transition diagram for machines.

where α, β, γ, δ, ε and ν are the transition probabilities from the three states given in Figure 1. Using the probability transition matrix and the limiting probability, we obtain each state's occurrence probability as follows:

$$\pi_j = \sum_{i=1}^{3} \pi_i p_{ij} \quad \text{for} \quad j = 1, 2, 3, \tag{7}$$

$$\sum_{j=1}^{3} \pi_j = 1. \tag{8}$$

Using these probabilities, we can compute the reliability of each state that helps us to assess the total reliability of the system.

We also can compute the long run probability for each state, using the steady state distribution given below:

$$\begin{bmatrix} A & B & C \end{bmatrix} \begin{bmatrix} 1-\alpha-\varepsilon & \alpha & \varepsilon \\ \beta & 1-\beta-\gamma & \gamma \\ \nu & \delta & 1-\delta-\nu \end{bmatrix} = \begin{bmatrix} A & B & C \end{bmatrix}, \tag{9}$$

having $A + B + C = 1$.

The same computations exist for AGVs different failure state, while we stated 2 states, i.e. we have two state probabilities and a 2×2 transition matrix.

Now, for reliability we have:

$$R(t) = 1 - F(t), \tag{10}$$

where $F(t)$ is the failure probability computed above as states' probabilities. Note that, we can compute the reliability in two cases, first for current state, and second for steady state. The numerical comparison of the two could be interesting.

Having the current state of the system by the Markovian model and by the means of neural network, we can compute the steady state probabilities.

Next, we review the artificial neural network and the backpropagation neural network for our proposed work. The reason is to find the difference between the accuracy of the two methods and determine the most effective one. It is obvious that the neural network can be more efficient due to its using past data in training stage.

The aim to compute the steady state probability and reliability is to obtain an estimation of the system availability for long run planning horizon. Therefore, it is significant for a decision maker to determine steady state reliability, using the corresponding probability, accurately.

4.1. Artificial neural network

Neural networks are being widely used in many fields of study. This could be attributed to the fact that these networks attempt to model the capabilities of human brains. Since the last decade, neural networks have been used as a theoretically sound alternative to traditional statistical models. Although Neural Networks (NNs) originated from mathematical neurobiology, the rather simplified practical models currently in use have moved steadily towards the field of statistics. A number of researchers have illustrated the connection of neural networks to traditional statistical models. For example, Gallinari et al. [35] presented analytical results establishing a link between discriminant analysis and multilayer perceptrons (MLP) used for classification problems. Cheng and Titterington [36] made a detailed analysis and comparison of various neural network models with traditional statistical models. They showed strong associations of feed-forward neural networks with discriminant analysis and regression models, and unsupervised networks such as self-organizing neural networks with clustering. Neural networks are being used in areas of prediction and classification, areas where regression models and related statistical techniques have traditionally been used. Ripley [37] discusses the statistical aspects of neural networks and classifies neural networks as one of the classes of flexible nonlinear regression models. Warner and Misra [38] present a comparison between regression analysis and neural network computation in terms of notation and implementation. They also discuss when it would be advantageous to use a neural network model in place of a parametric regression model, as well as some of the difficulties in implementation. Vach et al. [39] presented a comparison between feed-forward neural networks and logistic regression. The conceptual similarities and discrepancies between the two methods are also analyzed.

Artificial neural networks have been applied successfully to many manufacturing and engineering areas. Zhengrong et al. [40] used quadratic regressions to assess the results of neural network for improving the efficiency of fermentation process development. The results show that different sizes of neural nets within a certain range give an equally good prediction by using the "stopping training" technique, while quadratic regressions are sensitive to the size of the data sets. Smith and Mason [41] mentioned that regression and neural network modeling methods have become two competing empirical model-building methods. They compared the predictive capabilities of NNs and regression methods in manufacturing cost estimation problems.

4.1.1. The backpropagation neural network

The backpropagation algorithm trains a given feed-forward multilayer neural network for a given set of input patterns with known classifications. When each entry of the sample set is presented to the network, the network examines its output response to the sample input pattern. The output response is then compared to the known and desired output and the error value is calculated. Based on the error, the connection weights are adjusted. The backpropagation algorithm is based on Widrow-Hoff delta learning rule in which the weight adjustment is done through mean square error of the output response to the sample input. The general steps of backpropagation are given below:

1. Propagate inputs forward in the usual way, i.e. all outputs are computed using sigmoid thresholding of the inner product of the corresponding weight and input vectors. All outputs at stage n are connected to all inputs at stage $n+1$;
2. Propagate errors backwards by apportioning them to each unit according to the amount of the error the unit is responsible for.

We now discuss how to develop the stochastic backpropagation algorithm for the general case. The following notations and definitions are needed:

$\vec{x}_j$	Input vector for unit j ($x_{ji} = i$th input to the jth unit);
$\vec{w}_j$	Weight vector for unit j (w_{ji} = weight on x_{ji});
$z_j = \vec{w}_j.\vec{x}_j$	The weighted sum of inputs for unit j;
o_j	Output of unit j ($o_j = \sigma(z_j)$);
t_j	Target for unit j;
$Downstream(j)$	Set of units whose immediate inputs include the output of j;
$Output$	Set of output units in the final layer.

Since we are updated after each training example, we can simplify the notation somewhat by assuming that the training set consists of exactly one example, and so the error can simply be denoted by E.

We want to calculate $\frac{\partial E}{\partial w_{ji}}$ corresponding to each input weight, w_{ji}, of each output unit, j. Note first that since z_j is a function of w_{ji} , regardless of where in the network unit j is located,

$$\frac{\partial E}{\partial w_{ji}} = \frac{\partial E}{\partial z_j} . \frac{\partial z_j}{\partial w_{ji}} = \frac{\partial E}{\partial z_j} .x_{ji}, \tag{11}$$

furthermore, $\frac{\partial E}{\partial z_j}$ is the same, regardless of which input weight of unit j we are trying to update. So, we denote this quantity by δ_j.

Consider the case when j is an output unit. We know that:

$$E = \frac{1}{2} \sum_{k \in \text{Outputs}} (t_k - \sigma(z_k))^2. \tag{12}$$

Since the outputs of all units $k \neq j$ are independent of w_{ji}, we can then drop the summation and consider just the contribution to E by j, and we call it δ_j:

$$\delta_j = \frac{\partial E}{\partial z_j} = \frac{\partial}{\partial z_j} \frac{1}{2} (t_j - o_j)^2 = -(t_j - o_j) \frac{\partial o_j}{\partial z_j}$$

$$= -(t_j - o_j) \frac{\partial}{\partial z_j} \sigma(z_j) = -(t_j - o_j)(1 - \sigma(z_j))\sigma(z_j)$$

$$= -(t_j - o_j)(1 - o_j)o_j. \tag{13}$$

Thus:

$$\Delta w_{ji} = -\eta \frac{\partial E}{\partial w_{ji}} = \eta \delta_j x_{ji}. \tag{14}$$

Now, consider the case when j is a hidden unit. Like before, we make the following two important observations:

1. For each unit k downstream from j, z_k is a function of z_j.
2. The contribution to error by all units $l \neq j$, in the same layer as j, is independent of w_{ji}.

We want to calculate $\frac{\partial E}{\partial w_{ij}}$ for each input weight, w_{ji}, for each hidden unit j. Note that w_{ji} influences just z_j which influences o_j which influences z_k, $\forall k \in Downstream(j)$, each of which influences E. So, we can write:

$$\frac{\partial E}{\partial w_{ji}} = \sum_{k \in Downstream(j)} \frac{\partial E}{\partial z_k} . \frac{\partial z_k}{\partial o_j} . \frac{\partial o_j}{\partial z_j} . \frac{\partial z_j}{\partial w_{ji}}$$

$$= \sum_{k \in Downstream(j)} \frac{\partial E}{\partial z_k} . \frac{\partial z_k}{\partial o_j} . \frac{\partial o_j}{\partial z_j} .x_{ji}. \tag{15}$$

Again, note that all the terms, except x_{ji} in Eq. (15), are the same regardless of which input weight of unit j we are trying to update. Like before, we denote this common quantity by δ_j. Also, note that $\frac{\partial E}{\partial_k} \delta_k$, $\frac{\partial_k}{\delta o_j} w_{kj}$ and $\frac{\partial o_j}{\partial z_j} = o_j(1 - o_j)$. Substituting them in Eq. (13).

$$\delta_j = \sum_{k \in Downstream(j)} \frac{\partial E}{\partial z_k} . \frac{\partial z_k}{\partial o_j} . \frac{\partial o_j}{\partial z_j}$$

$$= \sum_{k \in Dowbnstream(j)} \delta_k . w_{kj} . o_j (1 - o_j), \tag{16}$$

we obtain:

$$\delta_k = o_j(1 - o_j) \sum_{k \in Downstream(j)} \delta_k . w_{kj}. \tag{17}$$

To adapt the backpropagation algorithm on our proposed model, consider the failure causes for machines and AGVs as inputs and the current state failure probability of machines and AGVs as outputs. We train the network collecting data in different time periods and compute the importance weight for each input resulting the corresponding output. A configuration of the proposed neural network is shown in Figure 2.

We are now in a position to state the backpropagation algorithm formally.

Algorithm 1: Formal statement of stochastic backpropagation.

(Training examples, η, n_i, n_h, n_o)

Each training example is of the form $\left\langle \vec{x}, \vec{t} \right\rangle$, where $\vec{x}$ is the input vector and $\vec{t}$ is the target vector, η is the learning rate (e.g., 0.05), n_i, n_h and n_o are the number of input, hidden and output nodes, respectively. Input from unit i to unit j is denoted by x_{ji} and its weight is denoted by w_{ji}. Create a feed-forward network with n_i inputs, n_h hidden units and no output units.

Initialize all the weights to small random values (e.g., between -0.05 and 0.05).

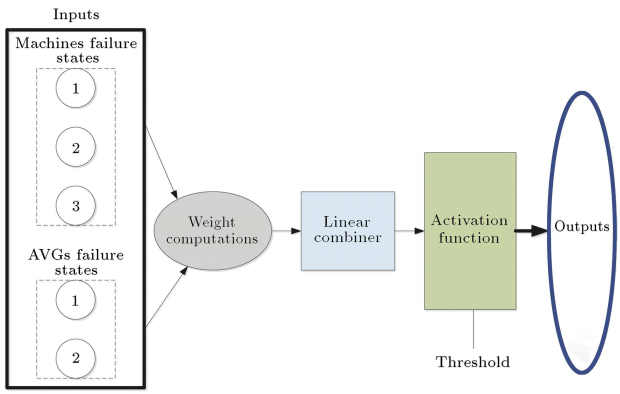

Figure 2. A configuration of the proposed neural network.

While termination condition is not met Do
For each training example $\left\langle \vec{x}, \vec{t} \right\rangle$,

1. Input the instance $\vec{x}$ and compute the output o_u of every unit.
2. For each output unit k, calculate,
$$\delta_k = o_k(1 - o_k)(t_k - o_k). \tag{18}$$
3. For each hidden unit h, calculate,
$$\delta_h = o_h(1 - o_h) \sum_{k \in Downstream(h)} \delta_k . w_{kh}. \tag{19}$$
4. Update each network weight w_{ji} as follows:
$$w_{ji} \leftarrow w_{ji} + \Delta w_{ji}. \tag{20}$$
where,
$$\Delta w_{ji} = \eta \delta_j x_{ji}. \tag{21}$$

This way, we can compare the performance of backpropagation neural network and limiting distribution model for computing the steady state probabilities, using the current state probabilities.

4.2. Mathematical optimization

Here, the mathematical optimization model is given. As stated before, we aim to maximize the total reliability of machines in shops in the whole jobshop system, and maximize the total reliability of the AGVs. Since the reliability model is stochastic, one may think about simulation study. But considering multiple-objectives and especially including cost factors in the form of a composite mathematical function is difficult and requires tiring and complicated simulation efforts. Also, as we will present further, we considered several 0.1 integer variables which are easier to be modelled mathematically.

4.2.1. Maximizing total reliability of machines

The following mathematical notations are employed to model this maximization problem:

Mathematical notations:

k	Index for machines,	$k = 1, ..., K$.
l	Index for jobs,	$l = 1, ..., L$.
m	Index for shops,	$m = 1, ..., M$.
R_k	Reliability of machine k.	

$$\tau_{kl} = \begin{cases} 1 & \text{if machine } k \text{ process job } l. \\ 0 & \text{otherwise.} \end{cases}$$

$$\varphi_{km} = \begin{cases} 1 & \text{if machine } k \text{ in shop } m \text{ is chosen.} \\ 0 & \text{otherwise.} \end{cases}$$

The mathematical model:
$$\text{Max} \sum_m \sum_k (R_k . \varphi_{km}), \tag{22}$$
s.t.
$$\sum_k \varphi_{km} . \tau_{kl} = 1, \qquad \forall l, m, \tag{23}$$
$$\varphi_{km} \in \{0, 1\}, \quad \forall k, m. \tag{24}$$

4.2.2. Maximizing total reliability of AGVs

The following mathematical notations are employed to model this maximization problem:

Mathematical notations:

n	Index for AGVs,	$n = 1, ..., N$.
R_n	Reliability of AGV n.	

$$\varsigma_{nm} = \begin{cases} 1 & \text{if AGV } n \text{ can service shop } m. \\ 0 & \text{otherwise.} \end{cases}$$

$$\zeta_n = \begin{cases} 1 & \text{if AGV } n \text{ is chosen.} \\ 0 & \text{otherwise.} \end{cases}$$

The mathematical model:
$$\text{Max} \sum_n R_n . \zeta_n, \tag{25}$$
s.t.
$$\sum_n \zeta_n . \varsigma_{nm} = 1, \qquad \forall m, \tag{26}$$
$$\zeta_n \in \{0, 1\}, \quad \forall n. \tag{27}$$

As a result, a multi-objective mathematical model is configured as follows:
$$\text{Max} \sum_m \sum_k (R_k . \varphi_{km}), \tag{28}$$
$$\text{Max} \sum_n R_n . \zeta_n, \tag{29}$$
s.t.
$$\sum_k \varphi_{km} . \tau_{kl} = 1, \qquad \forall l, m, \tag{30}$$
$$\sum_n \zeta_n . \varsigma_{nm} = 1, \qquad \forall m, \tag{31}$$
$$\sum_k \varphi_{km} = 1, \quad \forall m, \tag{32}$$
$$\zeta_n \in \{0, 1\}, \quad \forall n, \tag{33}$$
$$\varphi_{km} \in \{0, 1\}, \quad \forall k, m. \tag{34}$$

Next, an approach to optimize the proposed multi-objective model is given. We use objectives weighing method to integrate and optimize the model.

4.3. Analytic Hierarchy Process (AHP) for multi-objective optimization

To weight the objectives, we take a multi-criteria decision-making approach. Multi-Criteria Decision-Making (MCDM), dealing primarily with the problems of evaluation or selection, is a rapidly developing area in operations research and management science. AHP is a technique of considering data or information for a decision in a systematic manner. It is mainly concerned with a way of solving decision problems with uncertainties in multiple criteria characterization. It is based on three principles: constructing the hierarchy, priority setting, and logical consistency. We apply AHP to weight the objectives.

Construction of the hierarchy

A complicated decision problem, composed of various attributes of an objective, is structured and decomposed into sub-problems (sub-objectives, criteria, alternatives, etc.), within a hierarchy.

Priority setting

The relative "priority" given to each element in the hierarchy is determined by pair-wise comparisons of the contributions of elements at a lower level in terms of the criteria (or elements) with a causal relationship. In AHP, multiple paired comparisons are based on a standardized comparison scale of nine levels (see Table 1).

Let $C = \{c_1, ..., c_n\}$ be the set of criteria. The result of the pair-wise comparisons on n criteria can be summarized in an $n \times n$ evaluation matrix A in which every element a_{ij} is the quotient of weights of the criteria, as shown below:

$$A = (a_{ij}), \qquad i, j = 1, ..., n. \tag{35}$$

The relative priorities are given by the eigenvector (w) corresponding to the largest eigenvalue($\lambda_{\max}$) as:

$$Aw = \lambda_{\max} w. \tag{36}$$

When pair-wise comparisons are completely consistent, the matrix A has rank 1 and $\lambda_{\max} = n$. In that case, weights can be obtained by normalizing any of the rows or columns of A.

The procedure described above is repeated for all subsystems in the hierarchy. In order to synthesize the various priority vectors, these vectors are weighted with the global priority of the parent criteria and synthesized. This process starts at the top of the hierarchy. As a result, the overall relative priorities to be given to the lowest level elements are obtained. These overall, relative priorities indicate the degree to which the alternatives contribute to the objective. These priorities represent a synthesis of the local priorities, and reflect an evaluation process that permits integration of the perspectives of the various stakeholders involved.

Consistency check

A measure of consistency of the given pair-wise comparison is needed. The consistency is defined by the relation between the entries of A; that is, we say A is consistent if $a_{ik} = a_{ij}.\ a_{jk}$ for all i, j, k. The consistency index (CI) is:

$$CI = \frac{(\lambda_{\max} - n)}{(n-1)}. \tag{37}$$

The final Consistency Ratio (CR), on the basis of which one can conclude whether the evaluations are sufficiently consistent, is calculated to be the ratio of the CI and the random Consistency Index (RI):

$$CR = \frac{CI}{RI}. \tag{38}$$

The value 0.1 is the accepted upper limit for CR. If the final consistency ratio exceeds this value, the evaluation procedure needs to be repeated to improve consistency. The measurement of consistency can be used to evaluate the consistency of decision-makers as well as the consistency of all the hierarchies.

We are now ready to give an algorithm for computing objective weights using the AHP. The following notations and definitions are used:

n	Number of criteria;
i	Number of objectives;
p	Index for objectives, $p = 1$ or 2;
d	Index for criteria, $1 \leq d \leq D$;
R_{pd}	The weight of pth item with respect to dth criterion;
w_d	The weight of dth criterion.

Table 1. Scale of relative importance.

Intensity of importance	Definition of importance
1	Equal
2	Weak
3	Moderate
4	Moderate plus
5	Strong
6	Strong plus
7	Very strong or demonstrated
8	Very, very strong
9	Extreme

Algorithm 2: OWAHP (compute objective weights using the AHP)

Step 1: Define the decision problem and the goal.

Step 2: Structure the hierarchy from the top through the intermediate to the lowest level.

Step 3: Construct the objective-criteria matrix using Steps 4 to 8 using the AHP. (Steps 4 to 6 are performed for all levels in the hierarchy.)

Step 4: Construct pair-wise comparison matrices for each of the lower levels for each element in the level immediately above by using a relative scale measurement. The decision-maker has the option of expressing his or her intensity of preference on a nine-point scale. If two criteria are of equal importance, a value of 1 is set for the corresponding component in the comparison matrix, while a value of 9 indicates an absolute importance of one criterion over the other (Table 1 shows the measurement scale).

Step 5: Compute the largest eigenvalue by the relative weights of the criteria and the sum taken over all weighted eigenvector entries corresponding to those in the next lower level of the hierarchy.

Analyze pair-wise comparison data using the eigenvalue technique. Using these pair-wise comparisons, estimate the objectives. The eigenvector of the largest eigenvalue of matrix A constitutes the estimation of relative importance of the attributes.

Step 6: Construct the consistency check and perform consequence weights analysis as follows:

$$A=(a_{ij})=\begin{bmatrix} 1 & \frac{w_1}{w_2} & \cdots & \frac{w_1}{w_n} \\ \frac{w_2}{w_1} & 1 & \cdots & \frac{w_2}{w_n} \\ \vdots & \vdots & \ddots & \\ \frac{w_n}{w_1} & \frac{w_n}{w_2} & & 1 \end{bmatrix}$$

Note that if the matrix A is consistent (that is, $a_{ik}=a_{ij}.a_{jk}$, for all $i,j,k=1,2,...,n$), then we have (the weights are already known):

$$a_{ij}=\frac{w_i}{w_j}, \qquad i,j=1,2,...,n. \tag{39}$$

If the pair-wise comparisons do not include any inconsistencies, then $\lambda_{\max}=n$. The more consistent the comparisons are, the closer the value of computed $\lambda_{\max}$ is to n. Set the Consistency Index (CI) (which measures the inconsistencies of pair-wise comparisons) to be:

$$CI=\frac{(\lambda_{\max}-n)}{(n-1)},$$

Table 2. The objective-criteria matrix.

	C_1	C_2	...	C_d
Objective 1	R_{11}	R_{12}	...	R_{1d}
Objective 2	R_{21}	R_{22}	...	R_{2d}

Table 3. The criteria-criteria pair-wise comparison matrix.

	C_1	C_2	...	C_d	W_d
Criteria 1	1	a_{12}	...	a_{1d}	w_1
Criteria 2	$1/a_{12}$	1	...	a_{2d}	w_2
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
Criteria d	$1/a_{1d}$	$1/a_{2d}$	...	1	w_d

and let the Consistency Ratio (CR) be:

$$CR=100\left(\frac{CI}{RI}\right),$$

where n is the number of columns in A and RI is the random index, being the average of the CI obtained from a large number of randomly generated matrices.

Note that RI depends on the order of the matrix, and a CR value of 10% or less is considered acceptable.

Step 7: Form the objective-criteria matrix as specified in Table 2.

Step 8: As a result, configure the pair-wise comparison for criteria-criteria matrix as in Table 3.

The w_d are gained by a normalization process. The w_d are the weights for criteria.

Step 9: Compute the overall weights for the objectives, using Tables 2 and 3, as follows:

$$\begin{aligned}\psi &= \text{Total weight for objective 1}\\ &= R_{11}\times w_1+R_{12}\times w_2+...+R_{1d}\times w_d,\\ \psi' &= \text{Total weight for objective 2}\\ &= R_{21}\times w_1+R_{22}\times w_2+...+R_{2d}\times w_d,\end{aligned} \tag{40}$$

where $\psi+\psi'=1$. Thus the integrated objective function is formed as:

$$\text{Max}\left(\psi.\sum_m\sum_k(R_k.\varphi_{km})+\psi'.\sum_n(R_n.\zeta_n)\right)$$

5. Computational results

Here, a numerical example is worked out to imply the effectiveness and applicability of the proposed model. Using machines' (amateur operator, equipment deficiency, and inappropriate part specifications) and AGVs' (carrier overload and guide path fracture) failure probability transition matrices, and by the means of limiting probabilities, the states occurrence probabilities for each machine or AGV can be computed.

Also, note that the number of machines is 10, number of shops is 4, number of AGVs is 4, and number of jobs to be processed on a product is 8. Since eachs of the failure states mentioned causes breakdown of the system, the failure states are parallel. Using these probabilities, we can compute the reliability of each state, using Eqs. (1) and (2) which helps us to assess the total reliability of the system as follows:

Reliability (machine 1): 0.0124
Reliability (machine 2): 0.0303
Reliability (machine 3): 0.0435
Reliability (machine 4): 0.0054
Reliability (machine 5): 0.0641
Reliability (machine 6): 0.00398
Reliability (machine 7): 0.0287
Reliability (machine 8): 0.00703
Reliability (machine 9): 0.00239
Reliability (machine 10): 0.0197
Reliability (AGV 1): 0.0753
Reliability (AGV 2): 0.0639
Reliability (AGV 3): 0.0458
Reliability (AGV 4): 0.389

As we stated before, another way to compute the steady state probabilities is backpropagation neural network. The input of the system is given by a one dimensional vector, and the output is given by a two/three dimensional matrix. To facilitate the computations of backpropagation neural network, MATLAB 7.1 user interface, NNtool, is applied. A feedforward network is programmed with one input, ten hidden units with logistics activation function, and two/three outputs. Using the MATLAB 7.1 user interface NNtool, we insert the data and perform the required settings to train the data to obtain an appropriate pattern. Then, using the pattern, we can approximate the output of the proposed neural network. We used pseudo data for the neural network analysis.

Outputs:
Reliability (machine 1): 0.0133
Reliability (machine 2): 0.031
Reliability (machine 3): 0.045
Reliability (machine 4): 0.0063
Reliability (machine 5): 0.0628
Reliability (machine 6): 0.00377
Reliability (machine 7): 0.0281
Reliability (machine 8): 0.00723
Reliability (machine 9): 0.00243
Reliability (machine 10): 0.0184
Reliability (AGV 1): 0.0761
Reliability (AGV 2): 0.0652
Reliability (AGV 3): 0.0463
Reliability (AGV 4): 0.396

Clearly, backpropagation computations are slightly different from the steady state equation ones. Since neural network employs several training data sets to adapt the appropriate pattern, its results are more valid. A graphical comparison for the machines reliability computations, using two approaches, is shown in Figure 3. The machines that process different jobs are shown in Table 4. The AGVs that can service different shops are shown in Table 5.

Here, to solve the proposed multi-objective model, AHP, as explained in Section 4.3, is employed. The integration weights for the objectives are 0.43 and 0.57, respectively. Optimizing the above linear program in MATLAB 7.1, we obtain 1123.45, as the integrated

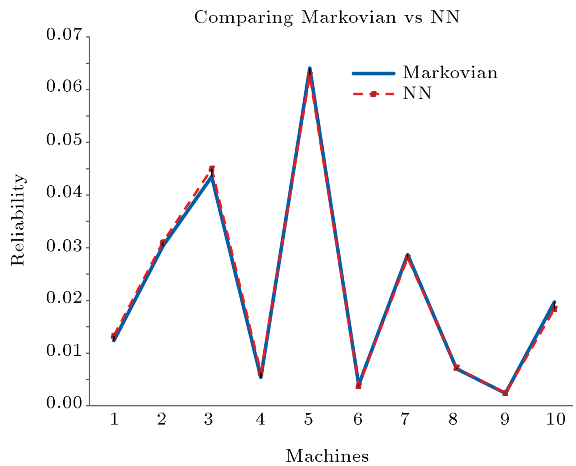

Figure 3. Graphical comparison for the machines reliability computations.

Table 4. The machines that process different jobs.

τ_{kl} / k \ l	1	2	3	4	5	6	7	8
1	0	1	0	0	0	1	0	0
2	0	0	0	0	1	0	1	1
3	1	1	0	0	0	0	0	0
4	0	0	1	1	1	0	0	0
5	0	0	1	0	0	1	0	1
6	0	0	1	1	0	0	0	0
7	1	0	0	1	0	0	0	0
8	1	1	0	0	1	0	0	0
9	1	1	0	0	1	0	1	0
10	0	0	1	0	0	0	1	1

Table 5. The AGVs that can service different shops.

ζ_{nm} / n	m	**1**	**2**	**3**	**4**
1		0	1	0	1
2		1	0	1	0
3		1	0	0	1
4		0	1	1	1

Table 6. The decision variables' values.

φ_{km} / k	m	**1**	**2**	**3**	**4**
1		0	0	0	0
2		0	0	1	0
3		0	0	0	0
4		0	0	0	0
5		1	0	0	0
6		0	0	0	0
7		0	0	0	0
8		0	1	0	0
9		0	0	0	0
10		0	0	0	1
ζ_n		1	2	3	4
-		1	1	0	0

objective functions' value and the decision variables' values are reported in Table 6.

The results show the machines to service the shops, and the chosen AGVs to service the shops aiming at maximizing the total reliability of machines in shops in the whole jobshop system, and maximizing the total reliability of the AGVs. The strategic viewpoint of such computations is to enable the management to control the failures of AGVs and machines to satisfy the optimization purposes. This way, the proposed multi-objective mathematical model was capable of functioning as a Markovian reliability assessment model.

6. Conclusions

We proposed a Markovian model for Flexible Manufacturing Systems (FMSs). The model considered two features of automated flexible manufacturing systems equipped with Automated Guided Vehicle (AGV), namely the reliability of machines and the reliability of AGVs in a multiple AGV jobshop manufacturing system. We made use of current state transition matrix for the failure of the machines and AGVs in different states. Therefore, a Markovian model was proposed for reliability assessment. Also, for steady state probability computations, the limiting theorem was compared with adapted backpropagation neural network, showing neural network's effectiveness. Using the reliabilities, we worked out an optimization mathematical model. The optimization objectives in the proposed model were maximizing the total reliability of machines in shops, in the whole jobshop system, and maximizing the total reliability of the AGVs. The computational results illustrated the applicability of our proposed model. A strategic viewpoint of such computations was to enable the management to control the failures of AGVs and machines to satisfy the optimization purposes.

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