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Contribution Overview to the Evaluation and Development of Spare Parts Management Models: Meta-Heuristic and Probabilistic Methods

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Abstract
The presence of the spare parts stock is a necessity to ensure the continuity of services. The supply of spare parts is a special case of the global supply chain. The main objective of our research is to propose a global spare parts management approach which allows decision makers to determine the essential points in stock management. Thus, it is important for the stock manager to evaluate the system considered from time to time based on performance indicators. Some of these indicators are presented in the form of a dashboard. The presentation of this chapter chronologically traces the progress of our research work. In the first part, we present the work related to the forecast of spare parts needs through parametric and statistical methods as well as a Bayesian modelling of demand forecasting. To measure the appreciation of the supply of spare parts inventory, the second part focuses on work related to the evaluation of the performance of the spare parts system. Thus, we concretize the link between the management of spare parts and maintenance in the third part, more precisely, in the performance evaluation of the joint -management of spare parts and maintenance, in order to visualize the influence of parameters on the system. In the last section of this chapter, we will present the metaheuristic methods and their use in the management of spare parts and maintenance and make an analysis on work done in the literature.

Keywords
Spare parts, maintenance, inventory management, probabilistic methods, metaheuristic methods, risk management, performance.

Introduction

The presence of the spare parts stock is a necessity to ensure the continuity of services. It must be managed throughout the life cycle of the property, respecting between financial and technical constraints. The supply of spare parts is a special case of the global supply chain. In order to ensure the availability of spare parts at a minimum cost and allow rapid replacement of faulty components and ensure continuity of services, the establishment of a reliable stock management system for this type of parts is put in place by starting the insurance problem intended to defend during the supply of parts, the cost of stopping resulting from a risk, by using insurance techniques.

An estimate of the cost of stopping a machine and the probability of the need for a given spare part are necessary to compare the cost of owning the parts and the risk of breakdown is made in order to make the stock management according to a calculation devoted to determining the protective stock. Despite the existence of a wide variety of inventory management models and several supply management policies in order to find the optimal quantity necessary to supply in acceptable time at lower cost, managing the stock of spare parts constitutes a the challenge and the choice of model and policy are not arbitrary. Depending on the needs, the stock manager decides the strategy without falling out of stock or having an overstock. The notion of uncertainties linked to the parameters for selecting spare parts exists in the management of these parts. It becomes predominant during the introduction of recycled spare parts or the integration of the repair principle.

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The main objective of the research work of the thesis (Bounou, 2019) is to propose a global approach to managing spare parts that allows decision-makers to determine the essential points in stock management. Thus, it is important for the stock manager to evaluate the system from time to time based on performance indicators. Some of these indicators are presented in the form of a dashboard.

In this context, we chose, based on the literature review, in the first axis of this work, to focus on statistical methods and modeling by Bayesian networks as being a decision tool for forecasting in spare parts needs since this step is considered among the most critical steps in the management of spare parts. In our work, we have taken into account the risks of shortage and obsolescence (aging) of spare parts. To assess the performance of spare parts management systems according to a policy, certain models make it possible to determine and calculate the performance indicators. Among the tools used in performance evaluation, graphical models (for example: Bayesian and Petri nets) are the most used by integrating the risks linked to the stock in a probabilistic way. In this sense, we orient in the second axis of our work towards the evaluation of performance through stochastic Petri nets taking into account on the one hand the same risks considered in forecasting and on the other hand maintenance management.

The presentation of this chapter chronologically traces the progress of the research work. We briefly describe each of the constituent sections of this chapter which is made up of three parts. In the first part, we present the work related to the forecast of spare parts needs through the most used and efficient parametric and statistical methods in the literature, thus a modeling of demand forecasting with a probabilistic graphical method, based on Bayesian networks, which allows to take into account the uncertainty and the fluctuations of the parameters which act on the management of the stock of spare parts. To measure the appreciation of the supply of spare parts inventory, the second part focuses on work related to the evaluation of the performance of the spare parts system. Thus, we concretize the link between the management of spare parts and maintenance in the third part, more precisely, in the performance evaluation of the joint management of spare parts and maintenance, in order to visualize the influence of parameters on the system. In the last section of this chapter, we will present the metaheuristic methods and their use in the management of spare parts and maintenance and make an analysis on work done in the literature.

Estimated need

In this part, we will present the work dedicated to an essential step in the management of spare parts which is the forecast of demand.

Statistical methods

According to the literature review established in the papers (Bounou et al., 2017a; Bounou, 2019), statistical tools based on history or classical methods, the most recognized are: linear regression, basic and modified Croston methods, simple and weighted moving average methods, exponential smoothing and finally the bootstrap method. The latter method consists in resampling an initial sample taken from the initial population (a large number of times (Boylan and Syntetos, 2010; Hasni et al., 2018) and gives better results than the exponential smoothing and the method Basic Croston (Willemain et al., 2004; Diallo, 2006; Zhou and Viswanathan, 2011; Syntetos et al., 2015).

(Bounou et al., 2018) applied and compared the bootstrap method with other methods such as the hybrid method proposed by (Lazrak, 2015). This hybrid method allows a combination of the characteristics of the parametric methods used in forecasting in order to reinforce the best method by the performance of others since there is not one method that completely outperforms the others. The parametric forecasting methods that are used in hybridization by (Lazrak, 2015), for example: exponential smoothing and the Croston method.

A comparison between the hybrid method and the bootstrap method is made by (Bounou et al., 2018; Bounou, 2019) using a statistical indicator: the mean square error (MSE). It is noted that each method has advantages and disadvantages as well as the hybrid method proposed by (Lazrak, 2015), gives better results. Thus, it is proposed to modify the type levels of the methods used in the hybrid method of (Lazrak, 2015) by integrating the bootstrap method. This modification is treated by (Bounou, 2019). The modification proposed is at the level of the integration of statistical methods like the bootstrap method. They apply the modified hybrid method in their case, and hybridize, first, two methods: the hybridization of the bootstrap method and the modified Croston method (SBA) or double exponential smoothing. After, they present the influence of the hybridization of the three methods.

The results, obtained from the hybrid method adopted in different cases using a program in RStudio, are presented in the following tables.

Table 1
Results of hybridization of bootstrap and modified Croston (SBA)

Periods	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
P_{11}	1	0.75	0.8333	0.875	0.8	0.8333	0.857	0.8125	0.778	0.75	0.773	0.792	0.769	0.75	0.7333	0.7812	0.794	0.805	0.816	0.875
P_{12}	0	0.25	0.1667	0.125	0.2	0.1667	0.143	0.1875	0.222	0.25	0.227	0.208	0.231	0.25	0.2667	0.2188	0.206	0.195	0.184	0.125
P_{21}	0	0.25	0.1667	0.125	0.2	0.1667	0.143	0.1875	0.222	0.25	0.773	0.208	0.231	0.25	0.2667	0.2188	0.206	0.195	0.184	0.125
P_{22}	1	0.75	0.8333	0.875	0.8	0.8333	0.857	0.8125	0.778	0.75	0.227	0.792	0.769	0.75	0.7333	0.7812	0.794	0.805	0.816	0.875
Forecasts	2	3	3	3	2	2	2	3	2	3	3	3	1	2	2	3	2	2	2	2

Table 2
Results of hybridization of bootstrap and double exponential smoothing

Periods	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
P_{11}	1	0.75	0.8333	0.875	0.8	0.8333	0.857	0.8125	0.778	0.75	0.727	0.75	0.77	0.75	0.7333	0.75	0.765	0.75	0.737	0.75
P_{12}	0	0.25	0.1667	0.125	0.2	0.1667	0.143	0.1875	0.222	0.25	0.273	0.25	0.23	0.25	0.2667	0.25	0.235	0.25	0.263	0.25
P_{21}	0	0.25	0.1667	0.125	0.2	0.1667	0.143	0.1875	0.222	0.25	0.273	0.25	0.23	0.25	0.2667	0.25	0.235	0.25	0.263	0.25
P_{22}	1	0.75	0.8333	0.875	0.8	0.8333	0.857	0.8125	0.778	0.75	0.727	0.75	0.77	0.75	0.7333	0.75	0.765	0.75	0.737	0.75
Forecasts	2	3	3	3	3	2	2	3	2	3	3	3	2	3	2	3	3	3	3	2

Table 3
Results of the hybridization of three methods

Periods	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
P_{11}	1	0.9	0.857	0.895	0.913	0.8667	0.882	0.9	0.8723	0.846	0.824	0.836	0.850	0.838	0.825	0.831	0.842	0.852	0.843	0.85
P_{12}	0	0	0	0	0.0416	0.0667	0.0571	0.049	0.0625	0.077	0.069	0.064	0.073	0.081	0.075	0.071	0.0667	0.062	0.058	0.056
P_{13}	0	0.1	0.133	0.1	0.08	0.0645	0.0555	0.071	0.0833	0.094	0.103	0.095	0.087	0.0933	0.1	0.094	0.0879	0.092	0.097	0.093
P_{21}	0	0	0	0	0	0.091	0.074	0.0625	0.054	0.095	0.08	0.078	0.071	0.0983	0.089	0.084	0.08	0.076	0.072	0.068
P_{22}	1	0.86	0.833	0.875	0.895	0.833	0.862	0.8823	0.846	0.818	0.8	0.811	0.793	0.777	0.768	0.78	0.792	0.802	0.811	0.82
P_{23}	0	0.14	0.167	0.125	0.105	0.08	0.0667	0.0857	0.102	0.111	0.12	0.13	0.138	0.140	0.144	0.137	0.129	0.123	0.117	0.112
P_{31}	0	0	0	0.154	0.10	0.833	0.0714	0.0667	0.1	0.1	0.127	0.117	0.107	0.102	0.123	0.114	0.1067	0.1	0.116	0.109
P_{32}	0	0	0	0	0.1	0.833	0.0714	0.0667	0.1	0.1	0.125	0.117	0.140	0.135	0.121	0.112	0.1052	0.1	0.091	0.086
P_{33}	1	1	1	0.875	0.8	0.846	0.8667	0.875	0.8	0.8	0.76	0.773	0.763	0.770	0.764	0.78	0.7948	0.8	0.797	0.808
Forecasts	2	3	3	3	2	2	2	2	1	2	3	3	1	2	2	3	2	3	2	2

With P_{ji}: Transition probability from methods j to i.

To compare the methods mentioned in this paper, we have chosen one of the statistical indicators that (Lazrak, 2015) has already used to compare the proposed hybrid methods. The chosen indicator is the Mean Squared Error (MSE) which determines the accuracy of the method considered. The statistical indicator, calculated by the formula (1).

$$MSE = \sum_{i=1}^{N} \frac{(F_i - D_i)^2}{N}, \tag{1}$$

where: N – number of periods of the horizon considered; F_i – value of the expected demand; D_i – value of the request in the history.

The conclusion adopted is that the results are improved according to the statistical indicator considered MSE, presented in Table 4, as well as the most precise of these methods is the method which consists in the hybridization of the bootstrap and modified Croston (SBA) methods itself. if we're adding other methods. In other way, the performance of the methods which influences the hybridization and it is not the number of methods. The last remark retained is that the hybrid methods, proposed by (Lazrak, 2015) and modified, were able to eliminate the zero values of the demand. This can reduce the risk of obsolescence, which leads to obsolete parts at the time of intervention and to a shortage of spare parts.

Table 4
MSE indicator calculated (Bounou, 2019)

Method	Bootstrap	Hybrid 2	Modified Hybrid		
			Bootstrap + SBA	Bootstrap + Lissage double	Bootstrap SBA + + Lissage double
MSE	0.679	0.354	0.3	0.5	0.3

SBA means the Croston method modified by (Syntetos and Boylan, 2001).

Bayesian modeling

Bayesian networks are a presentation of knowledge and inferences under uncertainty. They make it possible to construct joint probabilities for the construction of the desired conditional probabilities (Naim et al., 2007). According to (Ghorbel, 2013) and (Naim et al., 2007), Bayesian networks are broken down into two qualitative and quantitative descriptions. The use of probabilities in the quantitative description allows the uncertainty to be taken into account by quantifying the dependencies between the variables in the form of conditional probabilities. Apart from the criteria considered (the ease, the cost and the implementation time) in the choice of the method among the different existing in the literature, Bayesian networks are preferable to other methods thanks to the aspects of data acquisition, representation of knowledge through the graphic presentation of Bayesian networks, use of knowledge in several areas through the same model, quality of software supply (Naim et al., 2007).

In the papers (Bounou et al., 2017b; Bounou et al., 2019a; Bounou, 2019), they chose causal networks which are centered on the probabilistic quantification of causalities, since probabilistic state formalities allow probabilistic calculation and simulation of a discrete event system to which the management of spare parts would be assimilated. Using the reliability or forecasting and simulation methods, the model proposed by (Bounou et al., 2017b; Bounou, 2019), is based on references (for example (Ghorbel, 2013) and (Brown, 1964) who use Bayesian networks by adding other parameters and hypotheses such as the risk of obsolescence.

The goal is to find an optimal combination between the two types of spare parts (recycled and new), in terms of lead time while minimizing costs due to stock-outs and obsolescence. To validate the Bayesian model, proposed in (Bounou et al., 2017b; Bounou, 2019), and understand the principle of its operation, this model is applied to an industrial example. There are several tools for simulating Bayesian networks. The majority of these tools deal with discrete variables. In the application made in (Bounou et al., 2019a), the planning horizon is divided into periods in order to determine at the end of each period: the nature and quantities of the parts to be purchased, thus the overall cost d purchase of the decision including the cost of risk of stock-out. The application is made on a graphical interface called Unbbayes.

The remarks retained are that the decision differs from one period to another taking into account the utility nodes considered, than two parameters which have more influence on the decision, namely: the purchase costs and the deadlines d supplies for both types of spare parts.

After determining the type of parts to buy, the cost of the decision is calculated based on price fluctuations. The total cost of ownership includes the cost of purchase, the cost of storage and the cost of obsolescence. Thus, this cost is influenced by the uncertainty of lead time and demand. The total cost of ownership is influenced by the delivery time. When the latter exceeds the period provided for in the previous period, an additional cost is considered in the cost of possession.

A comparison of the results presented previously with the model developed by (Ghorbel, 2013). This comparison was presented in the article (Bounou et al., 2019a). The utility function associated with the total cost of ownership of the parts makes it possible to evaluate the decision made. This function is considered, in the model of (Bounou et al., 2017b; Bounou et al., 2019a; Bounou, 2019), as being a financial cost since it represents the costs borne and due to the presence spare parts inventory. The costs due to delay and obsolescence are part of the utility function which allows you to choose the optimal decision while minimizing these costs.

According to the results presented in (Ghorbel et al., 2014) and (Ghorbel, 2013) of the reference model, the comments made are that the decision not to buy the parts is the most frequent decision to have a value d maximum utility. However in the case of (Bounou et al., 2019a; Bounou, 2019), the decision to buy new or recycled parts is the most frequent. This is due to the added parameter: the risk of obsolescence which is linked to demand in the previous period is influenced by the cost.

The risk of obsolescence is linked to the lifespan of parts, dead stock and the technological development of parts and goods. Thus, it has an influence on the model of (Bounou et al., 2019a; Bounou, 2019), in a way of having less of the decision not to buy the parts. On the other hand, the delivery times of the parts during the period t directly influence the decision. During the period $t+1$, they influence the cost of purchasing parts through the additional costs. The difference between the models of (Ghorbel, 2013) and (Bounou et al., 2019a; Bounou, 2019), is about the delivery time. The latter is considered different for the two types of parts. Recycled and new parts are not delivered by the same supplier and do not have the same delivery time. This difference influences the decision in a way to specify what type of part to order based on the deadlines of the previous period.

From the comparison between a model based on the bayes rule with other methods, already made by (Bergman, 2014), the conclusion reached is that the bayes method is recommended for limited data and produces better performances than both methods. On the other hand, the bootstrap method is compared with a hybrid method of two conventional methods in paper (Bounou et al., 2018). So the two methods are very close in terms of performance. Among the remarks retained in this comparison are: the bootstrap method generates a cheaper cost than the Bayesian model because of the uncertain parameters and the market fluctuation taken into account in the modeling by Bayesian networks, the bootstrap method can eliminate or minimize the frequency of having zero demand based on historical data but without having considered other types of obsolescence such as dead stock and stoppage of production of spare parts. In summary, Table 5 shows the main differences between the two methods. Another comparison is made in (Bounou, 2019) between the Bayesian model and hybrid methods, one proposed by (Lazrak, 2015) and the other the modified hybrid method. Indeed, the comparison made at the level of the cost of acquisition is presented in Fig. 1. We note firstly that the hybrid

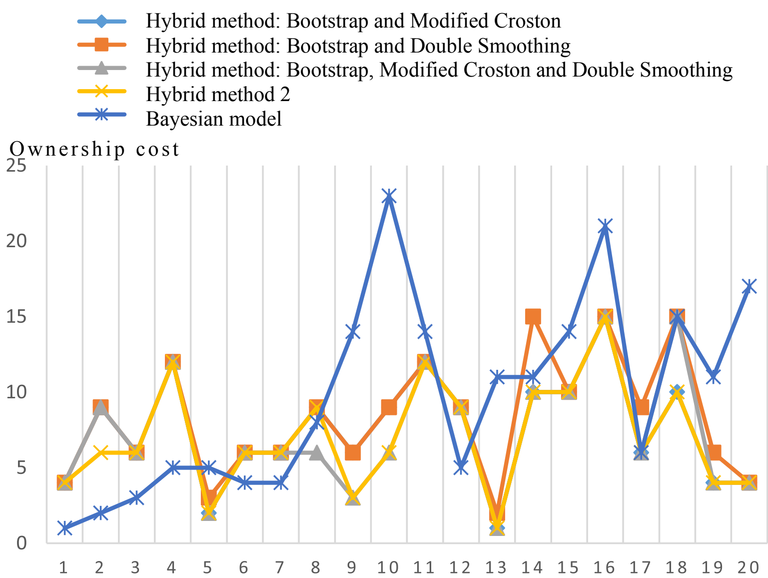

Fig. 1. Comparison of the ownership cost between the Bayesian model and the hybrid methods (Bounou, 2019)

methods, compared between them in thesis (Bounou, 2019), are close at the level of the cost. The conclusion reached is: The spikes in the Bayesian model compared to the other models return firstly to the risks of stock-out and obsolescence considered which cause additional costs if they occur, and secondly the variation of costs which depends on the availability of coins in the market. The Bayesian model knew a minimal cost compared to the other methods which confirms what has been said previously. The cost of ownership is influenced directly by demand, purchase costs, and indirectly by delivery time and availability in the market. Fluctuations in these uncertain parameters are not considered in all methods. Thus, some methods do not consider all of these parameters in the forecast.

Table 5
Difference between the bootstrap method and the Bayesian model (Bounou et al., 2019a; Bounou, 2019)

The bootstrap method	The Bayesian model
Fixed deadline	Variable time
zero demand	Obsolescence risk
Purchase cost not considered	Variation in purchasing costs
Confidence interval	The market fluctuation
Demand distribution	Uncertain parameters

Spare parts supply performance modeling

In this section we talk about assessing the performance of supply management of spare parts inventory. We start with a model, proposed in (Bounou et al., 2019b; Bounou, 2019), based on deterministic and stochastic batch Petri nets.

The application of stochastic Petri nets is used for modeling and performance analysis of discrete stochastic systems with batch behavior (batches of different sizes and variables) such as logistics systems, particularly the supply of stocks. In this context, (Labadi, 2005) developed an extension of the Petri nets which is the deterministic and stochastic Petri nets in batches. The components introduced into this type of Petri net are batch places, batch tokens and batch transitions.

The techniques for analyzing deterministic and stochastic Petri nets in batches, discussed by (Labadi, 2005), are divided into two types. The first type is qualitative analysis techniques, giving the possibility of researching essential network properties such as enumeration and invariant analysis techniques. The second type is the performance evaluation techniques, proposed by (Labadi, 2005), which are divided into two main approaches: An analytical approach based on the μ-mark graph manipulated simultaneously with the associated stochastic process characterized by a set performance indicators, An approach based on discrete event simulation is remarkable for complex systems to do an analytical study.

(Labadi, 2005) and (Fattah et al., 2016) applied the type of network developed and the techniques of analysis and evaluation on management policy (s, S). (Bounou et al., 2019b; Bounou et al., 2019c; Bounou, 2019) adopted one of the existing supply models by modifying the policy and integrating the concept of obsolescence, and evaluated it with the analytical and simulation studies using software (a graphical interface on Matlab).

In the analytical study of the model proposed and treated by (Bounou et al., 2019b; Bounou, 2019), the indicators established for assessing the performance of the management of spare parts supply are summarized in Table 6. Then, the behavior of these indicators is visualized in the papers (Bounou et al., 2019b) according to the delay and demand rates. The conclusions retained, based on the graphic presentation established in (Bounou et al., 2019b), are summarized:

- The average stock increases as the lead time increases, i.e. the lead time decreases. The average storage cost, its appearance, is similar to the average stock, since it suffices to multiply the latter by the unit storage cost. The frequency of supply increases as demand and lead times increase (delivery time decrease). The probabilities of empty stock and dead stock have the same appearance of difference in terms of values. The probability increases when the delay is great and if the demand increases.

The simulation study, for the spare parts supply model, is done in the papers (Bounou et al., 2019c; Bounou, 2019), at the graphical interface on Matlab dedicated to the Petri. In this study, the results obtained make it possible to quantify the influence of parameters on performance. (Bounou et al., 2019c; Bounou, 2019) treated three cases of parameter variation. The conclusions retained in these cases are summarized (Bounou et al., 2019c):

1st case: Variation of the replenishment threshold: the average stock varies slightly and experienced a peak which was the result of a decrease in the demand for maintenance service. The time of stock, demand and the frequencies of operations of the transitions are almost stable.

2nd case: Variation in the lead time: this case makes it possible to determine the point of intersec-

Table 6
The indicators expressions for spare parts supply management

The indicators	Expression
Average stock	$S_{moy}(\lambda_1,\lambda_2)=\dfrac{105736\lambda_2^2+98023\lambda_1\lambda_2}{36868\lambda_1^2+65405\lambda_1\lambda_2+24910\lambda_2^2}$
Average storage cost	$CS_{moy}=C_s*\dfrac{105736\lambda_2^2+98023\lambda_1\lambda_2}{36868\lambda_1^2+65405\lambda_1\lambda_2+24910\lambda_2^2}$
Empty stock probability	$Prob_{S=0}(\lambda_1,\lambda_2)=\dfrac{36868\lambda_1^2+35822\lambda_1\lambda_2}{36868\lambda_1^2+65405\lambda_1\lambda_2+24910\lambda_2^2}$
Supply frequency	$FA_{moy}(\lambda_1,\lambda_2)=\dfrac{36868\lambda_1^2\lambda_2+43200\lambda_1\lambda_2^2}{36868\lambda_1^2+65405\lambda_1\lambda_2+24910\lambda_2^2}$
Average ordering cost	$CC_{moy}(\lambda_1,\lambda_2)=C_c*\dfrac{36868\lambda_1^2\lambda_2+43200\lambda_1\lambda_2^2}{36868\lambda_1^2+65405\lambda_1\lambda_2+24910\lambda_2^2}$
Average purchase cost	$CA_{moy}(\lambda_1,\lambda_2)=C_a*\dfrac{213830\lambda_1^2\lambda_2+251822\lambda_1\lambda_2^2}{36868\lambda_1^2+65405\lambda_1\lambda_2+24910\lambda_2^2}$
Coverage rate	$TC(\lambda_1,\lambda_2)=\dfrac{105736\lambda_1\lambda_2^2+98023\lambda_1^2\lambda_2}{110604\lambda_1^2+196212\lambda_1\lambda_2+74730\lambda_2^2}$
Average cost of stock-out	$CR_{moy}(\lambda_1,\lambda_2)=C_{ru}*\dfrac{36868\lambda_1^2\lambda_2+35822\lambda_1\lambda_2^2}{36868\lambda_1^2+65405\lambda_1\lambda_2+24910\lambda_2^2}$
Probability of having a dead stock	$Prob_{DV=0}(\lambda_1,\lambda_2)=\dfrac{24465\lambda_1^2+30660\lambda_1\lambda_2}{36868\lambda_1^2+65405\lambda_1\lambda_2+24910\lambda_2^2}$
Obsolescence cost	$CO_{moy}(\lambda_1,\lambda_2)=C_{ob}*\lambda_2*Prob_{DV=0}(\lambda_1,\lambda_2)$

tion of the stock and the demand, which have opposite gaits which means that the stock covers the demand of the maintenance service. On the other hand, the residence time of the order varies inversely with the time.

3rd case: Variation in the rate of demand: two cases are treated in this variation for batch of size 1 or of size 2. For batch of size 1, a point of intersection of the paces of the stock and the demand of the maintenance service which is translated by an overshooting of the stock by the service request. For batch of size 2, there is a slight variation in the level of the average stock, on the other hand, a remarkable variation in the demand for the maintenance service which is reflected by an overrun in the frequency of crossing the transitions of the delivery of the service and of the delivery of the stock which means that the stock envelopes for a certain time the request of the maintenance service. The first point of difference between the two cases of variation in demand is: the excess of demand by the average stock or vice versa. On the other hand, the frequencies of the operations and the variation of the transitions of arrival of the demand is different in the two cases.

Joint management of spare parts stock and maintenance

Maintenance management provides an effective tool for managing preventive or curative activity, optimizing the production tool, and ultimately monitoring costs and performance (Bayarassou, 2010). According to the literature review made in (Bounou et al., 2017) on the joint management of spare parts and maintenance, the authors have developed models which are divided into two axes: the prediction of the necessary management parameters joint as the number of spare parts to order and the interval of the maintenance intervention, the evaluation of the performance of this management.

Among the models proposed for the evaluation of the performance of the maintenance service, the models which are based on Petri nets for example the model of (Abbou et al., 2001) which configured the performance analysis by the networks of Classic Petri dish, considering corrective and preventive interventions. In addition to these two types of maintenance, (Bounou et al., 2020a) took into account the risks of obsolescence and stock shortage in the evaluation of the performance of the joint management of spare parts and maintenance, in using deterministic and stochastic Petri nets in batches. So, based on the references (Bayarassou, 2010; Abbou et al., 2001; Bounou et al., 2019b), this model is treated by a numerical simulation study in the dedicated Matlab graphical interface. To this type of networks.

In this study, the results obtained make it possible to quantify the influence of the parameters on the performance in three cases of variation of parameters and the conclusions retained in these cases are summarized (Bounou et al., 2020a):

1st case: Variation in the rate of delivery of demand: on the one hand, the rate of debit, for places for preventive intervention, inventory, corrective intervention and repair of machines, experienced respectively a micro- variation and slight variation depending on the delivery time of the request for parts stored in the maintenance department. On the other hand, the actions of exit from the stock and the preventive intervention knew a micro-variation, on the other hand, the other transitions are slightly influenced. Thus, the appearance of the service rate for the transitions which model the unforeseen failure and the restart are similar, which is logical, since the two actions represent the beginning and the end of the maintenance intervention.

2nd case: Variation in the failure rate: the throughput rate, for the spaces that model the preventive intervention and the stock, experienced a micro-variation depending on the delivery time of the demand for parts stored in the maintenance department. On the other hand, the rate of flow of the place of the breakdowns of the machines knew a peak which means an overflow of the repair of the machines by the unexpected breakdowns. On the other hand, the failure rate influenced in the order of micro on the actions of exit of the stock and the order of the preventive intervention. The other transitions experienced a decrease.

3rd case: Variation in the preventive intervention rate: the throughput and service rates, respectively, for the different places and transitions of the model experienced a micro-variation depending on the preventive intervention rate.

Thus, we have oriented to analyze the influence of parameters on the indicators defined in the paper (Bounou et al., 2020b). The indicators established for assessing the performance of the joint management of spare parts and maintenance are summarized in Table 7. The definition of cost indicators for spare parts supply didn't change just we replaced the probability

Table 7
The indicators expressions for joint management of spare parts supply and maintenance

The indicators	Expression
Average stock	$S_{moy} = M(p1)_{moy} = \sum_{i=0}^{28} \pi_i * \mu(p1)$
Empty stock probability	$Prob_{S=0} = \pi_1 + \pi_{26} + \pi_{27} + \pi_{28}$
Supply frequency	$FA_{moy} = \lambda_2 * (\pi_1 + \pi_{24} + \pi_{25} + \pi_{26} + \pi_{27} + \pi_{28})$
Coverage rate	$TC = \lambda 1 * S_{moy}$
Average cost of stock-out	$CR_{moy} = C_{ru} * \lambda_2 * (\pi_1 + \pi_{26} + \pi_{27} + \pi_{28})$
Probability of having a dead stock	$Prob_{DV=0} = Prob\,(\mu(p6) = 1) = \pi_1 + \pi_{28}$
Obsolescence cost	$CO_{moy} = C_{ob} * \lambda_2 * (\pi_1 + \pi_{28})$
The frequency of unplanned failure	$FPI_{moy} = \lambda_6 * \pi_0$
The frequency of planned interventions	$FIP_{moy} = \lambda_{12} * \pi_0$
The repair frequency Corrective intervention Preventive intervention	$FRc_{moy} = \lambda_6 * \pi_3 + \lambda_{11} * (\pi_8 + \pi_{17} + \pi_{20} + \pi_{25})$ $FRp_{moy} = \lambda_{12} * \pi_2$
The interventions duration	$Di_{moy} = Di_u * (FRc_{moy} + FRp_{moy})$
The interventions quality Good repair: Bad repair:	$Q_{BR,\,moy} = \mu_{10} * (\pi_7 + \pi_{11} + \pi_{15} + \pi_{19} + \pi_{23})$ $Q_{MR,\,moy} = \lambda_{11} * (\pi_7 + \pi_{11} + \pi_{15} + \pi_{19} + \pi_{23})$
The costs of the interventions	$CI_{moy} = C_{\mathrm{r}} + C_{\mathrm{th}} * Di_{moy} + C_{\mathrm{p}} * (FPI_{moy} + FIP_{moy}) + C_{\mathrm{vpu}} * Q_{\mathrm{h}} * Di_{moy}$

by its updated expression. Also, the indicators are the indicators are based on the probability distribution of the states π_i. Then, the behavior of these indicators is visualized in the papers (Bounou et al., 2020b) according to the delay and demand rates. The conclusions retained, based on the graphic presentation established in (Bounou et al., 2020b), are summarized:

- The demand rate influences more on the majority of the indicators and the difference between these indicators is in the demand rate interval in which the indicators have large values. However, the delay rate which influences on the probabilities. The two repair rates influence on all the indicators in the same way. The large values of the preventive interventions rate increase the average stock, the coverage rate and the preventive interventions and repair frequencies. For the other indicators, they are influenced more by the unexpected failures rate which increases the values of the indicators. The test success rate influences, in order to increase the values of the indicators, on: the corrective interventions and repairs frequencies and the indicator of bad repair. For the others, they influenced by the repair again rate.

Metaheuristic methods

The different optimization methods which are classified into two main categories: exact resolution methods and stochastic methods. In this section we will present a vision on these methods and which ones are used in the management of spare parts.

The exact resolution methods

Some methods from the class of complete or exact algorithms, which give a guarantee of finding the optimal solution for an instance of finite size in a limited time and of proving its optimality (Hadibi, 2016).

The separation and evaluation method (Branch and Bound) is the separation and evaluation algorithm which is based on a tree-like method of finding an optimal solution by separations and evaluations, representing the solution states by a state tree, with knots, and leaves (Hadibi, 2016). It is based on three main axes (Hadibi, 2016). The first axe is the evaluation that makes it possible to reduce the search space by eliminating a few subsets which do not contain the optimal solution. The second axe is about separation which consists in dividing the problem into sub-problems. Thus, by solving all the subproblems and keeping the best solution found, we are sure to have solved the initial problem. It comes down to building a tree to list all the solutions. Finally, the route strategy which favors the vertices closest to the root by making fewer separations from the initial problem.

The Cutting-Plane method was developed and intended to solve combinatorial optimization problems (POC) which are formulated in the form of a linear program (PL). This method consists in solving a relaxed problem, and in adding iteratively constraints from the initial problem (Hadibi, 2016).

The method (Branch and Cut): The method of flat cuts is not always effective when faced with difficult problems. Similarly, although the "Branch and Bound" algorithm can be very efficient for a certain class of problems, for that we use the "Branch and Cut" method which combines between the 'Branch and Bound" algorithm and the flat cutting method. For a resolution of a linear program in whole numbers, the "Branch and Cut" method begins by relaxing the problem then applying the method of plane cuts on the solution found. If a whole solution is not obtained then the problem will be divided into several subproblems which will be solved in the same way (Hadibi, 2016).

The method of generating columns is based on the fact that not all the variables in a linear program will be used to reach the optimal solution. The objective of this method is to solve a reduced problem with a limited set of variables. The initial problem is called the master problem, and the reduced problem is called the restricted problem. The restricted problem is simpler to solve, but if the set of its variables does not contain those which give the optimal solution for the master problem, to reach the optimal solution of the master problem, it is necessary to add to the restricted problem variables which can be used to improve the solution. The problem of finding the best variable to add to the restricted problem is called the sub-problem associated with the master problem (Hadibi, 2016).

Mathematical methods are based on determining an optimum on the knowledge of a research direction often given by the gradient of the objective function with respect to the parameters. Among these methods, the conjugate gradient method, the quasi-Newton method, the SQP method and the Powell method (Hadibi, 2016).

Stochastic methods

Stochastic optimization methods are based on probabilistic and random transition mechanisms which indicate that several successive executions of these methods can lead to different results for the same initial configuration of an optimization problem (Hadibi, 2016). These methods have a great capacity to find the global optimum of the problem. Unlike most deterministic methods, they do not require a starting point or knowledge of the gradient of the objective function to reach the optimal solution (Hadibi, 2016). The following figure presents the most used stochastic methods which are defined below.

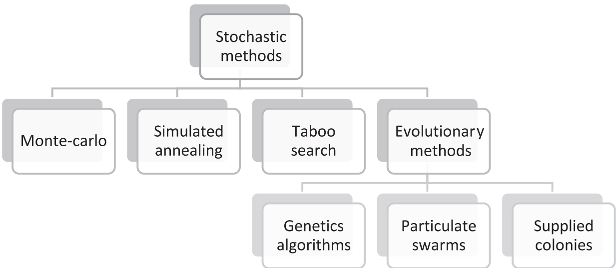

Fig. 2. Stochastic optimization methods (Hadibi, 2016)

Monte-Carlo is the simplest of the stochastic methods and consists in drawing a solution at random at each iteration. The objective function is evaluated at this point (Hadibi, 2016). If it is better than the current optimum, this value is recorded, along with the corresponding solution and the process continues until the shutdown conditions are verified (Hadibi, 2016).

Simulated annealing was introduced as a normal local search method, using a strategy to avoid local minima. This meta-heuristic is based on a technique long used by metallurgists (Hadibi, 2016). Simulated annealing is based on work done to describe the evolution of a thermodynamic system. The principle of simulated annealing is to iterate through the space of solutions (Hadibi, 2016).

Taboo search is a local search method combined with a set of techniques to avoid being trapped in a local minimum or the repetition of a cycle (Hadibi, 2016). This method has proven to be very effective in solving difficult optimization problems. Indeed, from an initial solution in a local solution set, solution subsets belonging to the neighborhood are generated (Hadibi, 2016). The algorithm sometimes accepts solutions that do not always improve the current solution (Hadibi, 2016).

Evolutionary methods are part of the last great class of stochastic methods. According to (Hadibi, 2016), they are based on an analogy with Darwin's theory of the natural evolution of species. They handle a set of solutions in parallel with each iteration. These include genetic algorithms, particle swarm optimization and ant colony algorithms. Unlike optimization techniques that explore space from a single point, evolutionary methods start from a set of configurations. The differences between these methods are linked to the representation of individuals and the evolution of the population. The differences between these methods are linked to the representation of individuals and the evolution of the population. Each of the methods is characterized by a particular evolution operator. Evolutionary methods are gradually asserting themselves as the most robust optimization techniques. They can be applied to a wide variety of problems because they are independent of the process to be optimized and do not use derivatives. Among the evolutionary algorithms, genetic algorithms occupy a special place because they bring together the three operators of selection, crossing and mutation.

Genetic algorithms

General principle

Genetic algorithms are optimization algorithms based on techniques derived from genetics and natural evolution: crosses, mutations, selection, etc. Genetic algorithms already have a relatively ancient history. A genetic algorithm searches for the extrema (s) of a defined function on a data space. To use it, you must have the following five elements according to (Hadibi, 2016):

- ***A coding principle*** for the population element makes it possible to associate a data structure with each of the points in the state space. This step generally takes place after a phase of mathematical modeling of the problem treated. The choice of data coding conditions the success of genetic algorithms. Binary coding was used extensively originally. Real codings are now widely used for the optimization of problems with continuous variables. There are two main types of coding: binary and real.
- ***A mechanism for generating*** the initial population must be capable of producing a non-homogeneous population of individuals which will serve as the basis for future generations. The choice of the initial population is important because it can make convergence towards the global optimum more or less rapid.
- ***A function*** to be optimized takes its values in R + and is called fitness or individual evaluation function. This is used to select and reproduce the best individuals in the population.
- ***Operators*** to diversify the population over generations and explore the state space. ***The crossover operator*** recomposes the genes of individuals existing in the population. The aim of ***the mutation operator*** is to guarantee the ex-

ploration of the state space. It brings to the genetic algorithms the property of ergodicity of space course which indicates that the genetic algorithm will be able to reach all the points of the space of state, without however traversing them all in the process of resolution.

- ***Design parameters***: population size, total number of generations or stopping criteria, probabilities of application of crossing and mutation operators.
- ***Principles of selection***: Selection makes it possible to identify statistically the best individuals in a population and to eliminate the bad ones. We find in the literature a large number of selection principles more or less adapted to the problems they deal with. The following two selection principles are most commonly used: Roulette selection and Stochastic selection.

Application in the management of spare parts

Metaheuristic methods are widely used in the field of planning and scheduling. For example, In order to establish efficient resolution methods for industrial scheduling problems, (Zinflou, 2004) brings a new point of view by integrating different concepts from multi-objective optimization, SIAD and genetic algorithms. He developed and implemented the different resolution approaches that form the basis of the model for the proposed interactive decision support system.

But, on the other hand, authors have used metaheuristic methods in the management of spare parts and maintenance, specifically genetic algorithms. So (Zerari and Mouss, 2009) used the evolutionary approach. In order to obtain an optimal solution, the method is obviously that of the complete enumeration of the search space which is in most cases prohibitive. It is in the form of an iterative global search algorithm in order to optimize the objective function by working in parallel on a population of chromosomes, distributed throughout the research space. The algorithm then starts with an initial population seeking the optimal combination of parameters corresponding to the best solution. (Zerari and Mouss, 2009) implemented the genetic algorithm, which in particular made it possible to appreciate the importance of the definition of the adaptation function in the optimization process. So, the strength of this algorithm by global exploration of the parameter space as much as it does not require any computation of derivatives or even without explicit knowledge of the working domain by simply manipulating bit strings and using simple operators . Thus, this force is most considered with the exponential rise in computer hardware.

The objective of the cost model corresponds to the periodic maintenance policy with minimum repair to failure proposed by (Hadibi, 2016), is to optimize the preventive maintenance of two mechanical systems, an RI80-5 compressor (single-part system) and a MGHK crane (multi-part system), by mobilizing the stochastic technique which is genetic algorithms in order to optimize the periodicity of partial revisions while minimizing the overall cost. The comparison of the solutions of the genetic algorithm with those of the deterministic methods and the results were satisfactory. The validation was done by an optimization tool provided by Matlab.

In order to find an optimal control policy which essentially depends on the quantity of spare parts to be kept in stock and the processing capacity of repair stations, (Bouzenad, 2017) took an interest in the analysis of the evolution of the spare parts management system in a permanent regime. To deal with multi-level logistics configurations, urgent requests in a higher level, and lateral transfers between stores of the same level, he has developed approximate models which are adjusted to cope with different service measures and to handle several spare parts references. They use heuristic methods in solving the proposed models. In order to allow managers to make informed decisions along the life cycle of the system, a very thorough comparative study has demonstrated the accuracy of the results obtained by its algorithms proposed and implemented with the best contributions published in the literature.

The objective of the work done by (Ayadi et al., 2010) is to propose, based on a modeling approach by dynamic Bayesian networks, a cost function allowing to evaluate maintenance policies, to implement an algorithm optimization of genetic type in order to select the optimal preventive maintenance policy. They proposed a cost function associated with a case study and a genetic algorithm-type optimization algorithm. The cost criterion considered naturally involves the essential parameters of maintenance.

Analysis and synthesis

According to the literature review done in the paper (Bounou et al., 2017), the most considered risk is a risk related to stock-outs. Variation in lead time and fluctuating demand are among the factors that lead to stockouts. The cost of shortage takes into account the downtime, lost profit and the cost of the rush order.

When forecasting spare parts needs using statistical methods, the remark made is that the bootstrap method is more efficient than the conventional methods. From the comparison of the bootstrap method with the hybrid method and the modified hybrid method, we deduce that the hybrid method improves the quality of forecasts and that the integration of the bootstrap method in the hybrid method gives better precision. So the performance of the methods that influence hybridization and not the number of methods.

Considering the risks of shortage and obsolescence and the lead time differ for the types of spare parts considered in Bayesian modeling, the conclusion reached, based on the comparison of the model with other methods, is that each methods have advantages and limits, for example, the bootstrap and hybrid methods do not take into account the fluctuations of the data and the risks, on the other hand, Bayesian networks allow to integrate the fluctuations of the data.

Regarding supply management according to a precise policy and performance evaluation, what is retained from the analytical and simulation studies made on the model proposed in the works: the change of the policy and the inspection of the service life (risk of obsolescence) influenced on the behavior of the stock, the added parameters influenced in a positive way on the behavior of the stock and more precisely the stock level which is improved compared to the existing one, and finally, the marking initial does not react on the performance in the simulation, on the other hand at the replenishment threshold, the supply time and the demand rate. The influence of obsolescence in the study of the system by simulation acts on the average stock and the transitions related to the placing and the supply of orders as well as on the demand of the maintenance service.

Finally, we discussed the model also based on the same type of Petri nets in order to show the link between the need for spare parts and maintenance interventions. This model makes it possible to simultaneously assess the performance of parts inventory management and maintenance (corrective and preventive). According to the simulation study, the visualization of the influence of some parameters, for example the failure rate and preventive intervention rate, on the behavior of the joint management system for spare parts and maintenance. Also, according to (Bounou et al., 2020b), the construction of performance indicators, in joint management, is based on the supply and maintenance parameters, on the other hand in the management of spare parts, their expressions are based only on the supply parameters.

From what we saw in this chapter, we can retain that stochastic methods are more efficient in both cases: either they are used as a resolution method, for example metaheuristic methods, or they are used in modeling, for example: Probabilistic graphic models (Bayesian networks, stochastic Petri nets, etc.).

In both cases, the cost is considered, but the difference is in the principle of operation of the methods. On the one hand, the metaheuristic methods are applied on a mathematical model (single objective or multi objective) with objective function which has the aim of minimizing the costs linked to the management of spare parts and maintenance according to the system considered. On the other hand, Bayesian modeling takes costs into account in a different way. Costs are considered as parameters influenced by other parameters of the system. Cost minimization, in Bayesian modeling, is done using utility functions. On the other hand, we have noticed that the stochastic principle and its use differ from one method to another. We illustrate this difference with the following examples:

- The bootstrap method: the demand forecast using this method is obtained with resampling based on the probabilities of the historical states;
- Bayesian networks use the probabilistic laws to characterize the parameters of the model to construct the tables of conditional probabilities of the nodes.
- Metaheuristic methods, specifically stochastic methods in their own way use probabilities or resampling, for example genetic algorithms. They make the crossing and mutation operators in a probabilistic way, the principles of selection statistically.

Conclusion

In this section, we have represented the contribution made in the thesis (Bounou, 2019) with the main objective of suggesting models for managing spare parts.

The work is oriented firstly in forecasting spare parts needs towards the best known statistical methods: the bootstrap method, and the hybrid method which combines the performance of conventional methods. From the comparison of the bootstrap method with the hybrid method and the modified hybrid method, we deduce that the performance of the methods that influence hybridization and not the number of methods. The work is secondly oriented towards probabilistic graphical methods which are widely used in forecasting demand taking into account the risks and uncertainty of the data. The conclusion reached is that each of the methods has advantages and limits.

Regarding supply management according to a precise policy and performance evaluation, we were able to retain, from the analytical and simulation studies made on the model proposed in the works, the parameters which influence the system. Next, we discussed the model also based on the same type of Petri nets in order to show the link between the need for spare parts and maintenance interventions. This model makes it possible to simultaneously assess the performance of parts inventory management and maintenance (corrective and preventive). A visualization of the influence of some parameters on the behavior of the joint management system of spare parts and maintenance was made in the study by simulation of the model.

Finally, in the last section of this chapter, we presented metaheuristic methods and their use in the management of spare parts and maintenance. From the analysis made, we noticed that stochastic methods are more efficient in both cases: either they are used as a resolution method, or they are used in modeling. We were able to determine the difference between these methods.

In perspective, we aim to detail the link between maintenance and production. We plan to integrate in our future works this link with spare parts management. So, we will treat the joint management of maintenance and spare parts by integrating the production plan. Also, we aim to deal with meta-heuristic methods in this axis.

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