Availability analysis of a two-component parallel system under stochastic dependence

Ziyad BAHOU
MOAD6,
Mohammadia School of Engineers,
Mohammed V University,
Rabat, Morocco
ziyad.bahou@hotmail.fr

Nizar ELHACHEMI
MOAD6, ABS,
Mohammadia School of Engineers,
Mohammed V University, UM6P
Rabat, Morocco
elhachemi@emi.ac.ma

Issam KRIMI
LAMIH,
BEAR Lab
International University of Rabat, Rabat Business School
Rabat, Morocco
issam.krimi@uir.ac.ma

Abdessamad Ait El Cadi
LAMIH, CNRS, UMR 8201, F-59313,
Université Polytechnique Haut-de-France, INSA Hauts-de-France
Valenciennes, France
abdessamad.aitelcadi@uphf.fr

Najiba SBIHI
MOAD6,
Mohammadia School of Engineers,
Mohammed V University,
Rabat, Morocco
sbihi@emi.ac.ma

Abstract

Research in maintenance engineering is increasingly focusing on complex systems in which components are subject to various dependencies, such as stochastic, structural, and economic dependences. This paper proposes a mathematical approach to calculate system's availability with stochastic dependence and assesses its effect on the system. From this perspective, Cox Proportional Hazards Model (CPHM), based on the exponential survival distribution, is used. The results show that increasing the degree of dependence impacts, considerably, system availability.

Keywords
Maintenance, availability, stochastic dependence, Cox Proportional Hazards Model.

1. Introduction

In recent years, social, economic, and technological constraints have led manufacturing companies to maximize the use of their production equipment, to satisfy the various demands. Consequently, the impact of the different dependencies between the components becomes more significant which makes its availability increasingly degraded. On the other hand, the main objective of any company is to maximize profits and minimize losses. Thus, the maintenance and production management strategies adopted are oriented to reduce costs and improve the production system's availability. For this purpose, it is necessary to take into account these dependencies, notably the stochastic dependence when calculating the availability for an optimal planning. One should know that the stochastic dependence occurs when the state of a component or its degradation can influence the states or degradation levels of other components. However, considering these interactions makes the availability estimation a little elusive for the elaboration of a correct predictive study. This study aims to propose an approach called" Cox proportional risk" for estimating Identify applicable funding agency here. If none, delete this. the availability of a component stochastically dependent on an another one in a given system. The CPHM is a class of survival models in statistics, whose use has been extended in several fields and situations. The main contributions of this paper are the following: (1) Mean time to failure (MTTF) modeling considering the interactions between the components; (2) An availability calculation based on the CPHM according to the exponential distribution; (3) Evaluation of the effect of the stochastic dependence on the system availability and on the exponential distribution proprieties; (4) A definition and a quantification of the stochastic dependence degree and finally, (5) Assessment of the repair rates as a function of dependence degree. With the above overarching mission, we have structured our paper as follows: Firstly, a literature review is presented in section 2. Then, we describe the problem in section 3. A presentation of Cox's proportional risk model and the availability formulation will follow in section 4. Subsequently, an analytical study is presented alongside their results in sections 5, and ultimately, a conclusion is provided in section 6.

2. Literature Review

In the literature, the main contributions on maintenance strategies are focused on the sequencing of the actions that characterize each strategy, thus focusing on the costs, the durations of these actions, the distributions of service life, and repair time. The maintenance strategies studied in a large part in a research field involve the search for optimal periods at which preventive actions should be executed, taking into consideration certain optimization criteria, such as the cost of maintenance, which must be minimized, or the availability of the equipment in question, which should be maximized for a finite or infinite horizon. In some cases, the objective has been to minimize costs under the constraint of availability or the opposite. In other cases, a joint optimization of costs and availability was considered. For a multi-component system, Do et al. (2015) have developed a heuristic based on genetic optimization algorithms and MULIFIT to obtain an optimal maintenance schedule under availability constraint and limited repairers over a rolling horizon. The impact of the last-named has been highlighted. Therefore, Bloch-Mercier (2000) was interested in the optimization of preventive maintenance for a repairable system based on stationary availability, which is calculated on the fact that the system is maintained with a finite state space, evolving in time following a semi-Markov process. They showed that, if the initial system has an increasing failure rate, maintenance actions improve stationary availability, and when they are not too long compared to repairs.

As availability is an intrinsic parameter in the maintenance planning optimization, external effects and internal interactions may occur in the system, and therefore impact the maintenance policies adopted. Viewed this way, Van Dijkhuizen and Van der Heijden (1999) analyzed the short-term effect of the availability fluctuations on the optimal preventive maintenance strategy by presenting a series of mathematical models and an optimization algorithm. In doing so, the optimal maintenance interval can be determined from the availability interval. In addition, Sinha et al. (2019) proposed a model for predicting the reliability/availability of a combined hardware software system at early design stages. Knowing that there are two types of interaction failures: "Software failures influenced by a Hardware failure" and "Hardware failures influenced by a Software failure". In this sense, Kumar et al. (2019) were interested in modeling the reliability and availability of repairable mechanical systems under structural dependence. For this reason, they proposed a Semi-Markov model and obtained the solutions using Monte Carlo simulation. Furthermore, Tsai et al. (2004) proposed a periodic PM policy based on the multi-component system availability. The effects of maintenance on reliability were formulated based on improvements in survivability. The PM interval of the system is then determined based on maximizing availability after the decided maintenance times. For its part, Yang and Tsao (2019) used matrix analysis to calculate steady-state availability and used Laplace transforms to obtain the reliability function, as well as the MTTF for a repairable system knowing that a repairer can intervene when a component fails. They used numerical data to evaluate the effects of system parameters on system reliability, MTTF and steady-state availability. De Smidt-Destombes et al. (2004) presented an approximate method to evaluate the interaction between repair capability, Spare parts, and preventive maintenance policy for a k-out-of-N system with an exponentially distributed component lifespan and repair times.

There are different types of dependence such as a stochastic dependence that occurs when the state of one component or its degradation can impact the states or degradation levels of other components. In other words, when the failure of one component affects the failure of another Structural dependence concerns systems composed of subsystems which are structured in block structure. This means that the maintenance of one failed component involves actions on other operational components. Economic dependency refers to the influence of component maintenance actions based on costs. This means that maintaining several components simultaneously is more economical or requires a shorter time than maintaining them separately. Multi-component systems with stochastic dependency are not yet particularly studied because of the difficulty of modeling these types of dependency. Zhou et al. (2016) were interested in the maintenance optimization of a parallel-series system considering the stochastic and economic dependency between the components, as well as the limited maintenance capacity by using the Factored Markov Decision Process (FMDP). They also developed an approximate linear programming (ALP) algorithm for the resolution. In the case where several components may fail or deteriorate simultaneously, this means that the deterioration acceleration of one component is associated with that of the other ones, and this is one of the stochastic dependency kinds called "common-mode deterioration". Likewise, an extended work of Feng et al. (2015) has been proposed by Keedy and Feng (2012), (2013), which is based on this type of dependence. The authors were interested in the reliability of multi-component stent systems, which are small tubular mesh devices that are inserted into the narrowed artery of a patient, which are configured in series because the overall system does not function when one of them fails. On the other hand, Zhang et al. (2014) stresses that the components share the load of the system; they formulated the problem as a Markov decision process (CDM) to minimize maintenance costs. In the same vein, they showed that the dependency between components must be considered when making a maintenance policy decision, for the costs related to the ignorance of this dependence increase significantly with the number of components and the dependence degree. Thus, they discussed a second type of stochastic dependency called Load sharing. Such is the case when the components of a generation system share the total load equally, and when one of these components fails, the others increase their production rates to compensate for the rate of the one that has failed. In their study, Zhang et al. (2018) investigated the third type of stochastic dependence called "failure-induced damage", where the failure of one component can cause damage to another, thereby accelerating its degradation. The authors analyzed respectively the expected warranty costs from the manufacturer's and the consumer's point of view of a two-component system operating in series with a stochastic dependence between the components. For this purpose, they have assumed that each time component 1 fails, random damage occurs on component 2, and that a component 2 failure causes a failure of the system. Component 2 fails when its total cumulative damage exceeds a predetermined level L.

Moreover, the maintenance planning optimization of multi-component systems is very complex and requires that the modelling and estimation of their availability and reliability be the most realistic possible. In order to achieve such a result, we must include in the models the effects of the dependencies mentioned in the paragraph above; however, this complexity makes the analytical methods very difficult to use. Hence, simulation methods are appropriate tools to address this problem. One of these methods is the Monte Carlo approach, which allows the modelling of the complex system behavior under realistic time-dependent operational conditions. A Monte Carlo simulation model has been proposed by Borgonovo et al. (2000) to evaluate maintenance policies and plant operation techniques under economic constraints related to several aspects, such as ageing, repair, obsolescence, and refurbishment. They introduced a Brown-Proschan model to describe ageing and an obsolescence model to evaluate the opportunity to replace a damaged component with a new and improved one. In Crespo Marquez et al. (2004), the authors proposed a general approach to the assessment of the reliability of the availability of complex systems, which includes the use of Monte Carlo simulation in a continuous time. Recently, Naseri et al. (2016) analyzed the availability of oil and gas processing equipment operating under Arctic conditions by adapting a Monte Carlo (MC) simulation approach, while taking into account the virtual age of system components and maintenance tasks. They characterized the impacts of influencing factors, such as human factors, logistical delays, and severe weather conditions on equipment reliability, maintainability, and spare parts supply plans.

To the best of our knowledge, no attention has been given to the problem in which the impact of stochastic dependence, on system' availability, is assessed using analytical methods. Therefore, in this study, we have studied a system with two components, one being stochastically dependent on the other. Consequently, a stochastic dependence impact evaluation is performing by calculating an influence factor called degree of dependence based on the failure history. This factor will be adopted when reformulating availability.

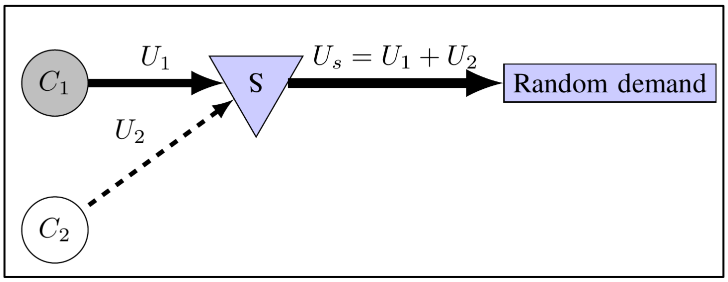

Figure 1. System description

3. Problem Description

We consider a production system consisting of two components (denoted as C_1 and C_2) producing a unique product. The figure 1 shows the different flows and production rates of the components (U_1 , U_2). The connection in this figure indicates that C_1 produces continuously and C_2 produces discontinuously depending on C_1's production rate and the demand. Its also displays the relationship between the components Production rates and the demand. In order to be satisfied, the demand must be equal to the sum of the two component production rates over a defined time horizon. Consequently, When the demand is high and the production rate of C_1 is insufficient to satisfy it, the additional demand is carried out on C_2. If C_2 failed, $C_1$is running at its maximum rate. However, a C_1failure stops the system immediately, whereas a C_2 failure only reduces the performance capacity of the system and accelerates its degradation (increase a C_1failure rate). C_2 can be considered as a subcontracting, a support, or a complementary component.

Components Failures occur following a known probability distribution with density function f_i (t). The time to repair is considered to be random according to a set of known probability distributions with density functions g_i (t). Each failure of C_2 causes a random damage or accelerate a deterioration within C_1.

Several real-world applications that experience this studied model, we find for example a systems subject to two dependent kind of failures as is the case of a hybrid system that couples an electric and thermal engine. Thus, the thermal engine failure stops the system immediately, whereas a electric one only reduces the performance capacity of the system and therefore increase the failure rate of the other.

In order to develop our approach, we propose the following assumptions:

1) C_1 is considered as the main component and therefore it constitutes the majority of the system (see figure 1).
2) Failure probability distributions are known for all the components.
3) The components are assumed to produce the same product.
4) The components is repaired with a random time with a given distribution function;
5) C_1 after corrective interventions is as good as new (perfect maintenance).
6) C_2 after corrective interventions is as bad as old (minimal repair).
7) We consider that C_1 is stochastically depending on C_2.

4. Availability for Scholastically Dependent System

In this section, a stochastic dependence is modeled according to the exponential distribution based on CPHM, and it is eventually considered in the availability formulation.

4.1 Dependence modeling

In our study we consider that the system is in a state of degradation when the C_2 component fails and is in fail state when C_1 is down. During system state of degradation, the C_1 component goes at maximum rates causing an accelerated deterioration, which is represented by the stochastic dependence. Thus, we consider C_1 be stochastically dependent on C_2. For this purpose, the covariate that affect the system availability is defined by X which is the state variable of C_2 as follows:

$$X = \begin{cases} 1 = & \text{if } C_2 \text{ is down} \\ 0 = & \text{if } C_2 \text{ is runing} \end{cases}$$

As it is previously indicated, we adopt the CPHM which is a survival analysis model and is similar to classical regression models in the sense that we try to relate an event to a number of explicative variables. It is widely used in several fields: B. Santana et al. (2020) used the Cox model to assess the reliability of a refinery's wastewater collection and transport system. Wan et al. (2019) have assessed with the risk of using peer-to-peer P2P platforms, which consists of providing loans directly to borrowers and investors in order to enable them to anticipate this risk. Chen et al. (2020) combine Cox model with deep learning to estimate TBF for predictive maintenance because the censoring and scarcity of data are considered as critical problem that can compromise performance estimation based on maintenance data. The Cox model is considered as a semi-parametric model, hence its popularity compared to the purely parametric models, because it does not require the specification of the baseline risk. It can be applied to any situation where the time of the occurrence of an event is being studied. This event can be the recurrence of an illness, death, breakdown, etc.

This model expresses the failure rate for system as follows:

$$\lambda_i(t|X) = \lambda_0(t)\exp(X\beta) \qquad (1)$$

Where $\lambda_0(t)$ represents the nominal failure rate which is a function of time only.
β is a factor of influence and its defined as dependence degree in our approach. The system reliability function according to Cox is expressed as follows:

$$R_i(t|X) = R_0(t)^{\exp(X\beta)} \qquad (2)$$

for a given system:

- If $\beta = 0$, no effect of X on the global risk of system λ (t|X).
- If $\beta > 0$, X increase the global risk of system λ (t|X).
- If $\beta < 0$, X decrease the global risk of system λ (t|X).

So, $\beta > 0$ implies that as the value of X increases C_2 failure increase), the system failure rate increases and thus its reliability decreases. In other word, a covariate X is positively associated to the system failure rate, and thus negatively associated to the system reliability. Then, this means that more β is greater, more the effect of the stochastic dependency is significant on failure rate, reliability, and availability of the system.

4.3 Availability formulation based on the exponential distribution

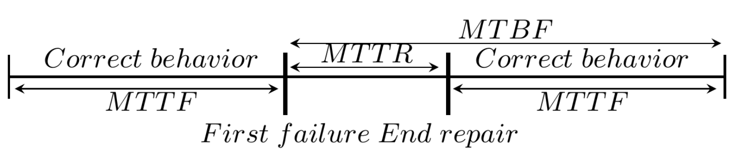

Figure 2. A schematic diagram of MTTF, MTTR, and MTBF

The objective of this work is to develop a set of availability expressions based on the degree of dependence β. The developed models consider the exponential distribution as basic failure laws. The availability can be expressed as follows (See figure 2):

$$\frac{MTTF}{MTTF + MTBF} \qquad (3)$$

This expression, simultaneously, considers the mean time between failures and the mean time to repair. However, it does not consider the effect of one component failure rate on the degradation of the second one. Thus, we introduced Cox's Proportional Hazard Model to model this effect, which is used for proposing an integrated maintenance policy. Given the failure rate distribution of the chosen exponential distribution, the probability density function on [0; +∞] is formulated as $f(x) = \lambda e^{-\lambda x}$,where λ is a real.
We can then deduce the mean time between failures by:

$$MTTF = \int_{0}^{+\infty} R_0(t)^{\exp(\beta)}\, dt \quad (4)$$

Where β is a real.
First, we calculate $R_0(t)$ the nominal reliability, which represents the probability of not having a failure during a given service time interval:

$$R_0(t) = P(X \geq a) = 1 - \int_{0}^{a} \lambda e^{-\lambda t}\, dt = e^{-\lambda a} \quad (5)$$

Where λ is a constant.
From the equations (4) and (5), we can deduce the MTTF:

$$MTTF = \int_{0}^{+\infty} R_0(t)^{\exp(\beta)}\, dt = \int_{0}^{+\infty} (e^{-\lambda t})^{\exp(\beta)}\, dt = \frac{1}{\lambda e^{\beta}} \quad (6)$$

Hence β maintains the stochastic dependence between C_1 and C_2.
From the equations (3) and (4), we can deduce the system availability considering the stochastic dependence as follow:

$$A_s = \frac{\int_0^{+\infty} R_0(t)^{\exp(\beta)}\, dt}{\int_0^{+\infty} R_0(t)^{\exp(\beta)}\, dt + MTTR_s} = \frac{\frac{1}{\lambda e^{\beta}}}{\frac{1}{\lambda e^{\beta}} + MTTR_s} \quad (7)$$

when the components are independents (β = 0) the system availability A_s^0 is expressed as follow (canonical form):

$$A_s^0 = \frac{\frac{1}{\lambda}}{\frac{1}{\lambda} + MTTR_s} \quad (8)$$

from the equations (7) and (8) we notice that the degree of the stochastic dependence directly affects the exponential law parameter λ. Therefore, if we set $\lambda_{dep} = \lambda e^{\beta}$, we can conclude that with increasing of β, λ_{dep} increase i.e the failure rate increase which may cause a loss of availability. Therefore, the equation (7) can express as follow:

$$A_s = \frac{\frac{1}{\lambda_{dep}}}{\frac{1}{\lambda_{dep}} + MTTR_s} \quad (9)$$

5. Results and Discussion

In the following, we summarize a set of numerical experiments to highlight the impact of β on A_s and μ_s. The system parameters are fixed as follows: Exponential (λ = 0; 0015), $MTTR_s$ = 5 hours.

Figures 3 illustrates the effect of stochastic dependence on the availability of A_s for different values of λ. We observe that A_s decreases when β increases. Moreover, its shows that the impact of this dependence is more important when the failure rate is high, i. e. for the same degree of dependence, a system with a high failure rate is more impacted. This is explained by the fact that the exponential law models the period corresponding to the product's useful life and is essentially characterized by its absence of memory. This absence of memory indicates that the remaining life of a component does not depend on its current age. Therefore, this law is used when the failure rate is constant during the lifetime of the product. Concretely, stochastic dependence effect increases the failure rate of a system with such lifetime properties.

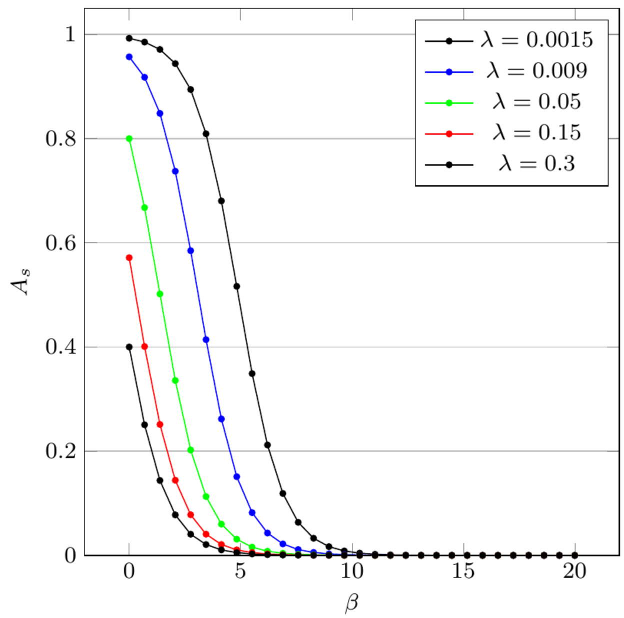

Figure 3. Impact of β on A_s with variation of λ

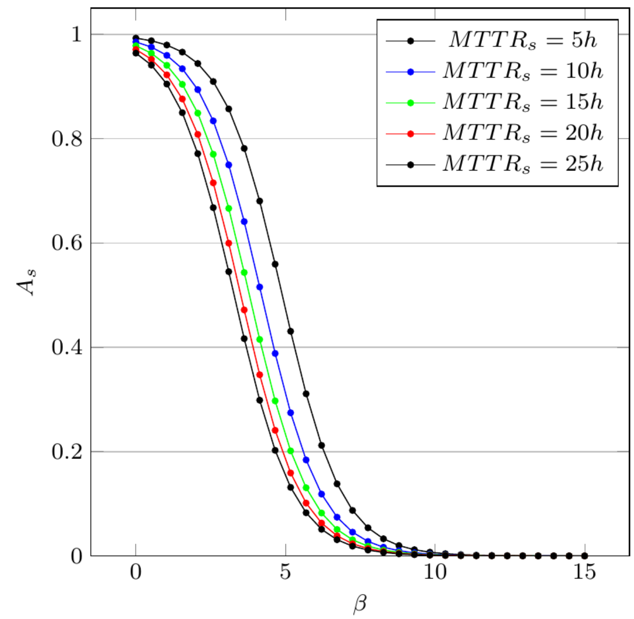

Figure 4. Impact of β on A_s with variation of $MTTR_s$

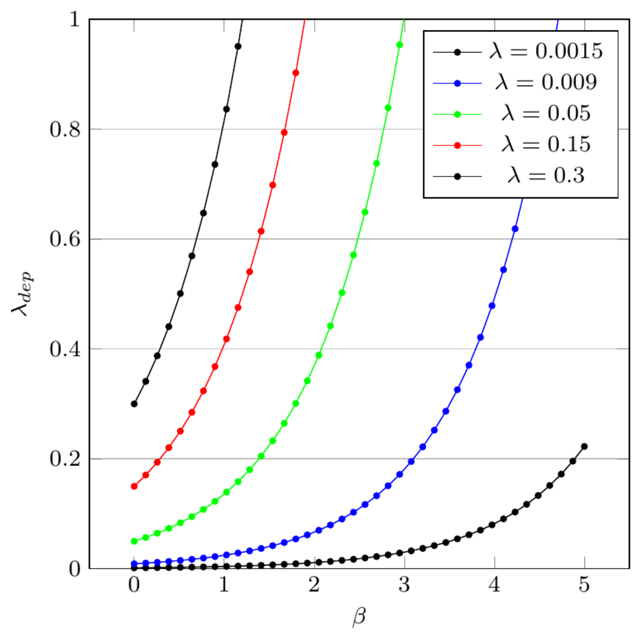

Figure 5. Impact of β on λ_{dep} with variation of λ

Figure 6 reveals that the failure rate increase with an increase of β and remains constant, which means that our approach preserves the same properties of the exponential law modeling according to the bathtub curve. Assuming that the system repair times follow an exponential distribution with a constant repair rate μ_s ($MTTR_s = \frac{1}{\mu_s}$), figure 4 illustrates the impact of β on A_s for different values of $MTTR_s$. We observe that we lose more availability in function of β in systems with a higher $MTTR_s$, this implies that in order to resist to this effect and to guarantee a given availability the repair rate μ_s must be important.

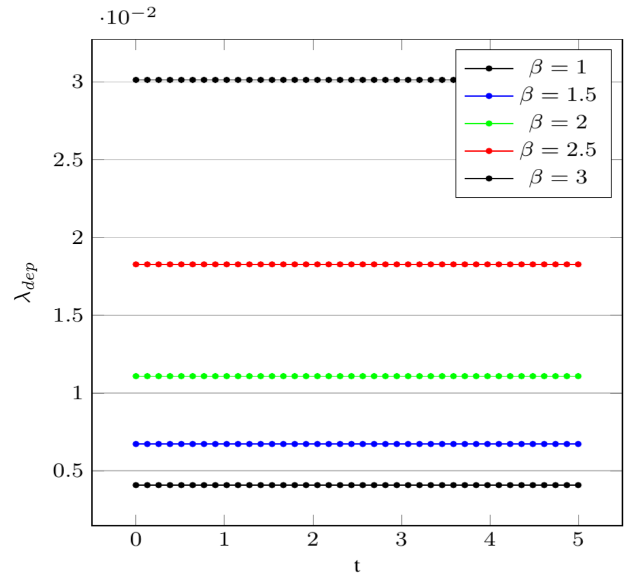

Figure 6. λ_{dep} trends with time and variations of β

For instance, it can be also noticed in the figure 5 that show the impact of β on λ_{dep} for different value of λ. We remark in this figure that the stochastic dependence has more impact on the system with high failure rate and makes of which the probability of failure more important. Therefore, this note completes the information contained in the figure 3. From the figures 3 and 4 we can conclude that the degree of dependence β is defined in the interval [0; 10].

Based on the previous analysis, we highlight the following observations: (i) The availability of system is impacted significantly by the stochastic dependence. This impact quantified by the CPHM; (ii) increasing the degree of dependence β considerably influences the availability of the entire system and consequently the availability of C_1 ; (iii) Intrinsically, this effect modifies the λ parameter of the exponential distribution meaning it increases with the degree of dependence; and (iv) the stochastic dependence has more impact on components that have a high probability of failure.

6. Conclusion

In this paper, we have proposed a mathematical approach of availability calculation for a parallel two-machine system with considering the stochastic dependence. The exposed procedure to evaluate the dependence's effect is based on the consideration of two functions. The first function, called the influence function, which defines the factors influencing availability 'dependency factor'. The second one, called basic time function. Thus, this approach makes it possible to evaluate the failure rate impact of one machine's failure rate on that of another with the time-dependent basic function (exponential distribution). Therefore, it makes possible to assess the impact of the failure rate of one machine on that of another. In this case, it shows the dependency's impact on the availability and repair rates of a machine stochastically dependent on another. Consequently, it is more realistic to consider these interactions when optimizing maintenance, production, or integrated optimization of these two functions. Hence, it is recommended to use such an approach as a starting point, to obtain a better assessment and estimation of the system availability, as well as a better planning of maintenance and production because in case of an incorrect estimation, a surplus of various unnecessary costs can be generated.

References

P. Do, H. C. Vu, A. Barros, and C. Bérenguer, ‘Maintenance grouping for multi-component systems with availability constraints and limited maintenance teams’, Reliab. Eng. Syst. Saf., vol. 142, pp. 56–67, Oct. 2015, doi: 10.1016/j.ress.2015.04.022.

S. Bloch-Mercier, 'Stationary Availability of a Markov System with Preventive Random Maintenance', p. 4.

G. van Dijkhuizen and M. van der Heijden, 'Preventive maintenance and the interval availability distribution of an unreliable production system', Reliab. Eng. Syst. Saf., vol. 66, no. 1, pp. 13–27, Oct. 1999, doi: 10.1016/S0951-8320(99)00013-7.

S. Sinha, N. Kumar Goyal, and R. Mall, 'Early prediction of reliability and availability of combined hardware-software systems based on functional failures', J. Syst. Archit., vol. 92, pp. 23–38, Jan. 2019, doi: 10.1016/j.sysarc.2018.10.007.

G. Kumar, V. Jain, and U. Soni, 'Modelling and simulation of repairable mechanical systems reliability and availability', Int. J. Syst. Assur. Eng. Manag., vol. 10, no. 5, pp. 1221–1233, Oct. 2019, doi: 10.1007/s13198-019-00852-3.

Y.-T. Tsai, K.-S. Wang, and L.-C. Tsai, 'A study of availability-centered preventive maintenance for multi-component systems', Reliab. Eng. Syst. Saf., vol. 84, no. 3, pp. 261–270, Jun. 2004, doi: 10.1016/j.ress.2003.11.011.

D.-Y. Yang and C.-L. Tsao, 'Reliability and availability analysis of standby systems with working vacations and retrial of failed components', Reliab. Eng. Syst. Saf., vol. 182, pp. 46–55, Feb. 2019, doi: 10.1016/j.ress.2018.09.020.

K. S. de Smidt-Destombes, M. C. van der Heijden, and A. van Harten, 'On the availability of a k-out-of-N system given limited spares and repair capacity under a condition based maintenance strategy', Reliab. Eng. Syst. Saf., vol. 83, no. 3, pp. 287–300, Mar. 2004, doi: 10.1016/j.ress.2003.10.004.

E. Borgonovo, M. Marseguerra, and E. Zio, 'A Monte Carlo methodological approach to plant availability modeling with maintenance, aging and obsolescence', Reliab. Eng. Syst. Saf., vol. 67, no. 1, pp. 61–73, Jan. 2000, doi: 10.1016/S0951-8320(99)00046-0.

A. Crespo Marquez, A. Sánchez Heguedas, and B. Iung, 'Monte Carlo-based assessment of system availability. A case study for cogeneration plants', Reliab. Eng. Syst. Saf., vol. 88, no. 3, pp. 273–289, Jun. 2005, doi: 10.1016/j.ress.2004.07.018.

M. Naseri, P. Baraldi, M. Compare, and E. Zio, 'Availability assessment of oil and gas processing plants operating under dynamic Arctic weather conditions', Reliab. Eng. Syst. Saf., vol. 152, pp. 66–82, Aug. 2016, doi: 10.1016/j.ress.2016.03.004.

Y. Zhou, T. R. Lin, Y. Sun, and L. Ma, 'Maintenance optimisation of a parallel-series system with stochastic and economic dependence under limited maintenance capacity', Reliab. Eng. Syst. Saf., vol. 155, pp. 137–146, Nov. 2016, doi: 10.1016/j.ress.2016.06.012.

Q. Feng, K. Rafiee, E. Keedy, A. Arab, D. W. Coit, and S. Song, 'Reliability and condition-based maintenance for multi-stent systems with stochastic-dependent competing risk processes', Int. J. Adv. Manuf. Technol., vol. 80, no. 9–12, pp. 2027–2040, Oct. 2015, doi: 10.1007/s00170-015-7182-3.

E. Keedy and Q. Feng, 'A physics-of-failure based reliability and maintenance modeling framework for stent deployment and operation', Reliab. Eng. Syst. Saf., vol. 103, pp. 94–101, Jul. 2012, doi: 10.1016/j.ress.2012.03.005.

E. Keedy and Q. Feng, 'Reliability Analysis and Customized Preventive Maintenance Policies for Stents With Stochastic Dependent Competing Risk Processes', IEEE Trans. Reliab., vol. 62, no. 4, pp. 887–897, Dec. 2013, doi: 10.1109/TR.2013.2285045.

Z. Zhang, S. Wu, S. Lee, and J. Ni, 'Modified iterative aggregation procedure for maintenance optimisation of multi-component systems with failure interaction', Int. J. Syst. Sci., vol. 45, no. 12, pp. 2480–2489, Dec. 2014, doi: 10.1080/00207721.2013.771759.

N. Zhang, M. Fouladirad, and A. Barros, 'Evaluation of the warranty cost of a product with type III stochastic dependence between components', Appl. Math. Model., vol. 59, pp. 39–53, Jul. 2018, doi: 10.1016/j.apm.2018.01.013.

S. P. B. Santana, K. P. Oliveira-Esquerre, R. W. S. Pessoa, and B. B. S. Silva, 'Reliability of a collection and transport system for industrial waste water', Process Saf. Environ. Prot., vol. 137, pp. 177–191, May 2020, doi: 10.1016/j.psep.2020.01.039.

J. Wan, H. Zhang, X. Zhu, X. Sun, and G. Li, 'Research on Influencing Factors of P2P Network Loan Prepayment Risk Based on Cox Proportional Hazards', Procedia Comput. Sci., vol. 162, pp. 842–848, 2019, doi: 10.1016/j.procs.2019.12.058.

C. Chen et al., 'Predictive maintenance using cox proportional hazard deep learning', Adv. Eng. Inform., vol. 44, p. 101054, Apr. 2020, doi: 10.1016/j.aei.2020.101054.

Biographies

Nizar El Hachemi received his PhD in Operation Research from Polytechnic School of Montreal. Currently, he is a Professor at EMI. Recently, he was promoted to the rank of HDR. He developed hybrid solution methods for solving transportation problem encountered in forestry by taking advantage of constraint programming, constraint-based local search and linear integer programming. Recently, he has developed effective heuristic integrators for solving rich problems in collaboration with several researchers from the Interuniversity Research Centre on Enterprise Networks, Logistics and Transportation (CIRRELT).

Abdessamad Ait El Cadi: Engineer from the Ecole Nationale des Ponts et Chaussées, with a MSc.A. & Ph.D. degrees in Industrial Engineering from Ecole Polytechnique de Montreal, he is also member of the association "Anciens ENPC (Ecole Nationale des Ponts et Chaussés)", member of ISG - Institute of Sound Management, Member of the OIQ - Order of Engineers of Quebec. Currently, he is Assistant Professor in Computer science at the LAMIH UMR CNRS 8201 research lab of the Université Polytechique Hauts-de-France (France) and INSA Hauts-de-France. With 18 years of experience in university teaching and training (~ 5000 h in Logistics, Industrial Engineering, Operational Research, Optimization, Computer Science and Mathematics), also professional experiences in the fields of Industrial Engineering, Logistics and Supply Chain. He has developed key experiences in optimization (metaheuristics, combinatorial optimization, exact methods (PL, PLNE ...), simulation, data mining, statistical analysis, logistics, supply chain, operations management and information systems design. He is, also, active in scientific research with many publications, reports and conferences.

Dr. Krimi Issam is an Assistant Professor of Supply Chain Analytics. He obtained Ph.D. from Polytechnic University of Hauts de France, France. He served as R&D analyst in collaboration with MIT before joining OCP Group as a Program Lead for Supply Chain Innovation. Dr. Krimi teaches Project Management, Information Technology Management, and Business Analytics. His research interests focus on developing efficient mathematical models and algorithms for production scheduling, maintenance planning and port-related operations planning. He attended several conferences and published articles, appeared in journals, such as Journal of Global Optimization, RAIRO and others.

Ziyad Bahou holds a MS degree in industrial engineering, from LORRAINE University in Metz, France. He is actually a PhD student at Department of industrial engineering with Research Team in modeling and decisions support for systems at Ecole Mohammadia d'Ingénieurs (EMI), Mohamed V University, Morocco. He is interested in operations research. His work is focused, more specifically, on fleet management and vehicle scheduling problem.