Proceedings of the 7th European Conference of the Prognostics and Health Management Society 2022 - ISBN – 978-1-936263-36-3

Artificial-intelligence-based maintenance scheduling for complex systems with multiple dependencies

Van-Thai Nguyen, Phuc Do, and Alexandre Voisin

Université de Lorraine, CNRS, CRAN, F-54000 Nancy, France
van-thai.nguyen@univ-lorraine.fr
phuc.do@univ-lorraine.fr
alexandre.voisin@univ-lorraine.fr

ABSTRACT

Maintenance planning for complex systems has still been a challenging problem. Firstly, integrating multiple dependency types into maintenance models makes them more realistic, however, more complicated to solve and analyze. Secondly, the number of maintenance decision variables needed to be optimized increases rapidly in the number of components, causing computational expensive for optimization algorithms. To face these issues, this thesis aims to incorporate multiple kinds of dependencies into maintenance models as well as to take advantage of recent advances in artificial intelligence field to effectively optimize maintenance polices for large-scale multi-component systems.

1. MOTIVATION AND RESEARCH PROBLEM STATEMENT

Due to higher demand in performance and safety, modern engineering systems nowadays are often composed of many components, where different inter-component dependencies can exist (Keizer, Flapper, & Teunter, 2017). Omitting component dependencies in maintenance modeling could result in high maintenance cost and suboptimal maintenance plan. Therefore, it is necessary to integrate them into maintenance models.

Maintenance policies can be classified into corrective (CM) and preventive (PM) strategy. CM carries out maintenance actions on failed machines, which is usually associated with high related costs due to unexpected production losses as well as unscheduled maintenance costs. In contrary, PM aims at maintaining functioning machines to prevent sudden failures, hence, to reduce downtime costs. PM interventions can be planned either in time-oriented or condition-based manner (CBM). However, the later appears to be more advantageous. Particularly, it allows to proactively make maintenance decisions based on degradation states of maintained machines instead of on a fixed calendar. Moreover, recent advances in sensing and information technology allow rich degradation data to be collected enabling CBM to become a popular and sophisticated approach for maintenance decision-making and optimization.

Whereas CBM optimization processes might be effectively achieved for single-unit systems due to the small number of decision variables needed to be optimized, the ones for multi-component systems suffer from the curse of dimensionality. Specifically, the number of decision variables grows rapidly as the number of components increases, causing computational expensive for optimization algorithms (Zhang & Si, 2020). Fortunately, recent advances in the field of artificial intelligence (AI) open a new direction to solve large maintenance decision-making problems. Therefore, how to take advantage of these advances to effectively plan maintenance actions for complex systems is a crucial issue.

Based on the above analysis, the objective of this thesis is to leverage AI techniques to optimally schedule maintenance operations for large-scale multi-component systems taking into account the impact of component dependencies.

2. THE STATE-OF-THE-ART

2.1. Component dependencies

Component dependencies fall into three primary groups which are economic, structure and stochastic dependence (Nicolai & Dekker, 2008). The economic dependence means that the joint cost of maintaining a group of several components is not equal to the cost of maintaining them separately. The structural dependence implies that repairing one component requires at least dismantling or maintaining other units.

Component stochastic dependence might be triggered by the failure or degradation levels of one component (failure- and degradation-based stochastic dependence). The number of studies investigating the later is small in comparison to the one studying the former. Several of them are reviewed in the following. The stochastic dependence characterized by state-state interactions meaning that the degradation evolution of a component is a function of its own state as well as other components' state, is studied in (Rasmekomen & Parlikad, 2014) for an industrial cool box in which component degradation is modeled using Gaussian process. The state-rate interaction, which implies that degradation levels of a component accelerate the degradation process of its dependent components, is investigated in (Bian & Gebraeel, 2014) for a networked system using a system of continuous stochastic differential equations, and in (Do, Assaf, Scarf, & Iung, 2019) for a gearbox system whose component degradation processes are described by Gamma processes. More recently, (Wang, Li, Chen, & Liu, 2022) investigated the impact of the degradation acceleration of one component on the degradation rate of other components (rate-rate interactions) in a continuous way over time for general multi-component systems using Wiener process. It can be noticed that the aforementioned articles describe the degradation-based stochastic dependence based on continuous stochastic processes. *Hence, there is still a gap in modeling such kind of stochastic dependence using discrete stochastic processes.*

Moreover, almost all existing maintenance models consider only one specific kind of dependency since integrating more than one makes them more complicated to analyze as well as more difficult to solve (Keizer et al., 2017). However, multiple dependency types in practice exist in many systems. For example, a gearbox system is studied in (Do et al., 2019), which suffers from both economic and stochastic dependence. *Therefore, incorporating multiple kinds of dependencies into maintenance models is necessarily taken into account.*

2.2. Maintenance optimization

CBM policies can be divided into two main groups: direct mapping and threshold-based policy. While the former maps directly from component degradation measurements to maintenance actions, the later first compares component states to predefined thresholds, and then choose maintenance actions accordingly. As mentioned previously, CBM optimization for multi-component systems suffers from the curse of dimensionality that causes computation expensive for optimization algorithms.

Recent advancements in the field of reinforcement learning (RL) give rise to direct mapping approaches by providing new tools to deal with maintenance decision optimization for large-scale systems. Particularly, deep RL algorithms (DRL) are employed to minimize maintenance costs for systems with extremely large state spaces showing better performance in comparison to threshold-based policies (Huang, Chang, & Arinez, 2020). However, DRL algorithms belong to the class of single-agent RL algorithms that is shown in literature to suffer from the problem of large action spaces. Fortunately, the framework of multi-agent DRL (MADRL) appears as a promising solution to this challenge, which has been received recently increasing attention from maintenance researchers (Huang et al., 2020; Andriotis & Papakonstantinou, 2021). *Consequently, how to take advantage of MADRL algorithms to effectively optimize maintenance decisions of large-scale multi-component systems is a crucial issue..*

Furthermore, it is vital in maintenance decision optimization to correctly define the objective function that often requires the system maintenance cost model. From a practical point of view, repair actions are usually grouped in each maintenance intervention due to the economic dependence between maintained components, which leads to the fact that individual costs, such as setup cost, spare part cost, labor cost, costs of maintaining each component are not recorded separately, instead, only total cost is documented. As a result, the requirement of separately collecting individual maintenance costs to construct the cost model at system level in almost all existing maintenance decision optimization algorithms used for multi-component systems is less practical. *Therefore, it raises the need for constructing a system cost predictor that can get rid of the demand of accessing individual maintenance costs.*

3. Expected Contributions

To support the scientific issues analyzed in the state-of-the-art section, the expected contributions are identified as belows:

1. Take advantage of AI techniques to solve practical maintenance decision-making problems.
2. Propose maintenance models taking into consideration multiple dependency types.
3. Propose approaches for modeling the degradation-based stochastic dependence using discrete stochastic processes.
4. Develop and/or improve MADRL algorithms to optimize effectively maintenance decisions of large-scale multi-component systems.

4. Achieved works

An AI-based framework is proposed in (Nguyen, Do, Voisin, & Iung, 2021) for maintenance decision-making in the case of unknown cost model at system level *(expected contribution 1)*.

The proposed framework consists of two main stages which are offline training and online decision-making as depicted in figure 1. The former aims at optimizing maintenance polices based on collected data, and the later involves realizing optimized polices. Moreover, the first stage is composed of two main phases. The first one aims to learn system cost model using artificial neural networks, and to estimate component degradation probability transition matrices. The objective of the second phase is to first construct learning envi-

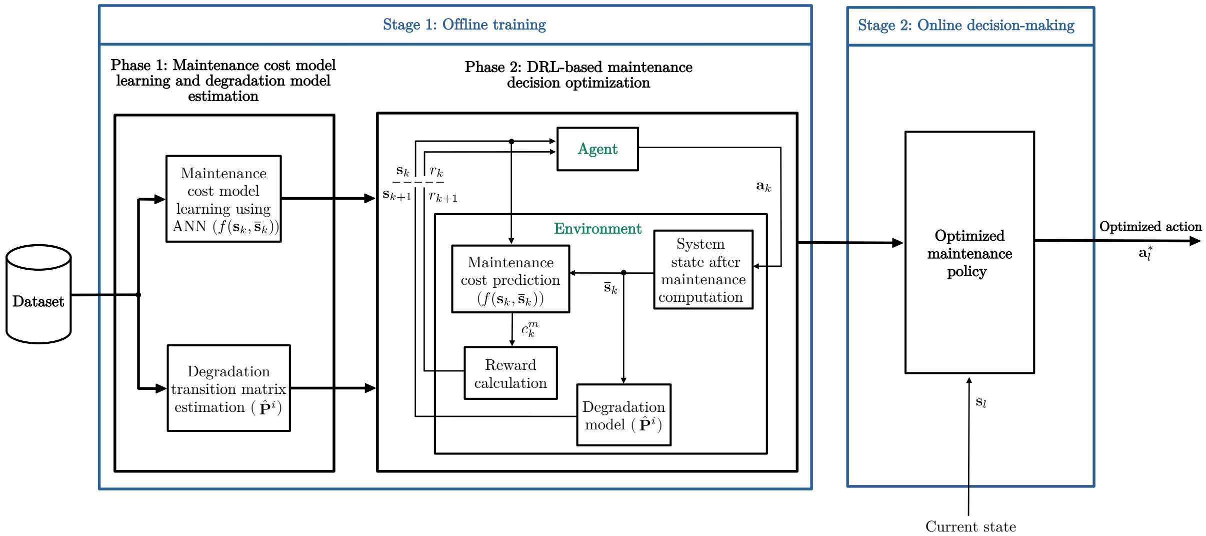

Figure 1. Illustration of AI-based maintenance framework for multi-component systems.

ronments dedicated to DRL algorithms employing the trained cost models and estimated transition matrices from the first phase, and then to train DRL agents to optimize maintenance decisions by letting them interact with the constructed environment. For more details about the framework, please take a visit to (Nguyen et al., 2021).

5. Current Works

The current works focus on maintenance planning for multi-component systems suffering from economic and stochastic dependence *(expected contribution 2)*. The economic dependence is described by two levels of setup cost sharing: system setup cost caused by administrative handling or transportation of spare parts, and component-type setup cost originated from the requirement of specific tools or repairman skills.

The stochastic dependence through state-rate interactions is modeled using a new approach based on the framework of Markov decision processes *(expected contribution 3)*. Figure 2 illustrates the degradation interactions in a two-component system in which each component has four condition states. It can be noticed that when a component degrades to a more serve state, its dependent components tend to degrade faster since their probabilities of staying in current states decrease while their probabilities of transitioning to worse conditions increase.

In order to take *the fourth expected contribution* into account, we customize a MADRL algorithm, namely WQMIX (Rashid, Farquhar, Peng, & Whiteson, 2020), in the case where system states can be fully observed to obtain cost-effective policies. Indeed, the algorithm takes advantage of the branching dueling network architecture (Tavakoli, Pardo, & Kormushev, 2018) to allow achieving linear increase in the size of the

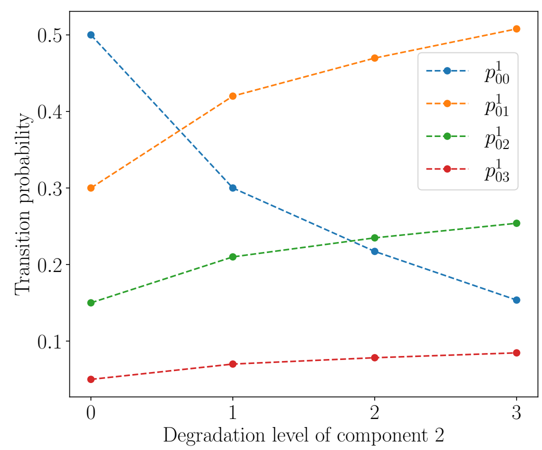

Figure 2. Changes in transition probabilities of component 1

output layer of deep Q-networks when the number of system components grows and the monotonic decomposition scheme for joint action-value functions (Rashid et al., 2020) to enable maintenance decision-making consistency at component and system level.

A comparative experiment is conducted on a 5-component system to verify the performance of the customized algorithm as well as to investigate the impact of component dependencies on optimized policies. The experimental results depicted in figure 3 show that BDQ (a MADRL algorithm also uses the branching network) and Dueling DDQN (a DRL algorithm) are incapable of approaching the optimal policy obtained by the customized WQMIX and VI (a dynamic programming algorithm), however, the optimization time of the customized algorithm (2 hours) is much less than the one of VI (9 hours). Moreover, it can be noticed that the optimal policy has an incentive to perform maintenance actions frequently and in groups due to the impact of component economic and stochastic dependence.

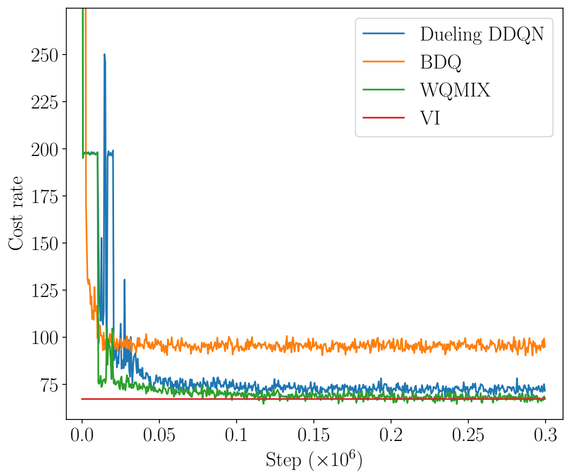

Figure 3. Evolution of cost rates during training

6. Conclusions

In this paper, the thesis's objective is identified, which is to take advantage of AI techniques to optimally schedule maintenance for large-scale multi-component systems taking into account the impact of component dependencies. To support this research direction, an AI-based framework is proposed in (Nguyen et al., 2021) to tackle maintenance decision-making in the case of unknown system cost models. The current works focus on modeling maintained systems with discrete-state components which suffer from stochastic and economic dependence as well as on customizing MADRL algorithms to effectively optimize maintenance decisions of large-scale systems.

The thesis's future work will focus on modeling methods that can integrate all three dependency types into maintenance models. Improving the learning speed of MADRL algorithms will also be considered.

Acknowledgment

This thesis is part of the AI-PROFICIENT project which has received funding from the European Union's Horizon 2020 research and innovation program under grant agreement No 957391.

References

Andriotis, C., & Papakonstantinou, K. (2021). Deep reinforcement learning driven inspection and maintenance planning under incomplete information and constraints. *Reliability Engineering & System Safety*, *212*, 107551.

Bian, L., & Gebraeel, N. (2014). Stochastic framework for partially degradation systems with continuous component degradation-rate-interactions. *Naval Research Logistics (NRL)*, *61*(4), 286–303.

Do, P., Assaf, R., Scarf, P., & Iung, B. (2019). Modelling and application of condition-based maintenance for a two-component system with stochastic and economic dependencies. *Reliability Engineering & System Safety*, *182*, 86–97.

Huang, J., Chang, Q., & Arinez, J. (2020). Deep reinforcement learning based preventive maintenance policy for serial production lines. *Expert Systems with Applications*, *160*, 113701.

Keizer, M. C. O., Flapper, S. D. P., & Teunter, R. H. (2017). Condition-based maintenance policies for systems with multiple dependent components: A review. *European Journal of Operational Research*, *261*(2), 405–420.

Nguyen, V. T., Do, P., Voisin, A., & Iung, B. (2021). Reinforcement learning for maintenance decision-making of multi-state component systems with imperfect maintenance. In *Proceedings of the 31st european safety and reliability conference.*

Nicolai, R. P., & Dekker, R. (2008). Optimal maintenance of multi-component systems: a review. *Complex system maintenance handbook*, 263–286.

Rashid, T., Farquhar, G., Peng, B., & Whiteson, S. (2020). Weighted qmix: Expanding monotonic value function factorisation for deep multi-agent reinforcement learning. *Advances in Neural Information Processing Systems*.

Rasmekomen, N., & Parlikad, A. K. (2014). Optimising maintenance of multi-component systems with degradation interactions. *IFAC Proceedings Volumes*, *47*(3), 7098–7103.

Tavakoli, A., Pardo, F., & Kormushev, P. (2018). Action branching architectures for deep reinforcement learning. In *Proceedings of the aaai conference on artificial intelligence* (Vol. 32).

Wang, Y., Li, X., Chen, J., & Liu, Y. (2022). A condition-based maintenance policy for multi-component systems subject to stochastic and economic dependencies. *Reliability Engineering & System Safety*, *219*, 108174.

Zhang, N., & Si, W. (2020). Deep reinforcement learning for condition-based maintenance planning of multi-component systems under dependent competing risks. *Reliability Engineering & System Safety*, *203*, 107094.