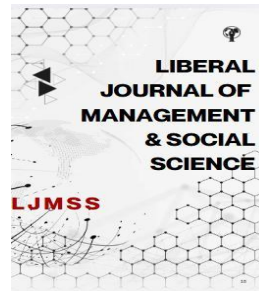


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INTEGRATED PRODUCTION AND MAINTENANCE DECISION-MAKING UNDER EQUIPMENT DEGRADATION: IMPLICATIONS FOR OPERATIONAL PERFORMANCE

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ABSTRACT

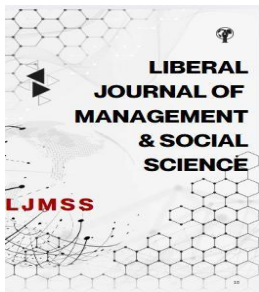
Co-ordinating production and maintenance activities is essential in manufacturing systems but more so under a state of machine deterioration. Previous studies emphasized that additions between such decisions are essential in minimizing cost and maximizing productivity besides leading to an improved reliability of the system (Gharbi & Kenné, 2005; Nourelfath & Châtelet, 2012). Yet, most methods either ignore for the complexity of degradation dynamics, or do not consider machine deterioration as a random process. This paper formulates a Markov Decision Process (MDP) model to solve the integrated production-maintenance scheduling with degradation uncertainty. The goal is to optimize the tradeoff between production throughput and preventative maintenance intervention, while minimizing downtime and associated longterm costs. MDP facilitates explicit modeling of the probabilistic state transitions between machine health statuses which in turn supports making robust decisions under uncertainty (Puterman, 2014; Cassady & Kutanoglu, 2003). Results indicate that the proposed model is far superior to conventional periodic maintenance, static schedule approaches in terms of imminent total cost and system availability. The results indicate that such MDP frameworks can effectively be adapted to real-world dynamic production environments, where uncertainty is a significant factor (Bai & Yun, 2021). For practitioners, managerial practices are given that may be adopted by firms wishing to improve operational resilience and increase the life of equipment via data driven integrated scheduling strategies.

Keywords: Production scheduling, preventive maintenance, machine degradation, Markov Decision Process, stochastic optimization, system reliability.

INTRODUCTION

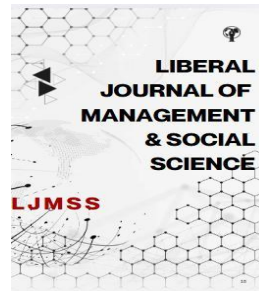
There is, however, an inherent compromise: a trade-off between the maximization of production rate and the preservation of machine reliability by means of acceptable maintenance. An on the other, the company are constantly challenged to drive increased volume while satisfying variable customer demand. Then again, machines wear over time, and the risk that they will break down grows in line with such gradual wear, causing downtime and defective products as well as a decrease of operating efficiency. It is therefore also of utmost importance to have the right mix between production and maintenance in order to make sustainable the industrial performance (Gharbi & Kenné, 2005). This has gained further importance in the age of digital manufacturing and Industry 4.0, with predictive maintenance and data-driven decision-making becoming more and more determinant for the competitiveness of companies (Bokrantz et al., 2020).

Although the coordination of decision-making is critical here, it has been commonly



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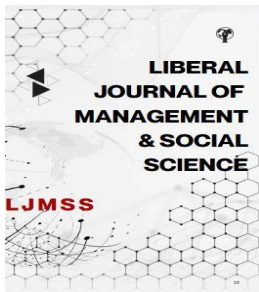
pursued in the classical manner of treating production scheduling and maintenance planning as separate optimization problems. Production always wants to maximize utilization and meet demand due dates, while maintenance often tries to minimize breakdowns and be reliable. The absence of coordination can lead to inefficient resource allocation and increased exposure to unplanned outages that disrupt production plans and inflate the cost of operations (Sloan et al., 2010). This enforced fragmentation has created inefficiencies, especially in rigged-gear or capital-intensive sectors such as automotive, aerospace and semiconductor manufacturing where equipment downtime creates expensive losses.

In order to address these limitations, integrated models for production and maintenance have become the focus of attention. Initial studies in this field were dominantly established based on deterministic models assumed constant degradation and failure risks, or in certain cases approximated these using maintenance schedules (Aghezzaf et al., 2007). Though useful to gain understanding, these models were unable to deal with the actualities of real-life conditions enshrining uncertainty and variability. Recent work applies stochastic optimization algorithms since degradation and failure are natural processes with inherent probabilities involved. For example, Noureldath and Châtelet (2012) showed that by considering stochastic models to account for the uncertain degradation, demand and repair times a more reliable maintenance policy could be derived.

But there are also substantial problems with the research which has been done. Several stochastic models are based on periodic assumptions or heuristic policies which, while easy to implement from a computational point of view, do not effectively represent the mutual impact of machine health and production scheduling decisions. For instance, under periodic maintenance a machine is maintained at constant time intervals even if it is in healthy state which could result not only to untimely failures but also needless maintenance (Chelbi & Ait-Kadi, 2004). Heuristic driven solutions, on the other hand, are not optimal and their performance could degrade in dynamic production environments. As a result, there is no doubt that there is clear demand for frameworks capable of incorporating degradation dynamics into scheduling decisions in a mathematically tractable manner with computationally feasible methods.

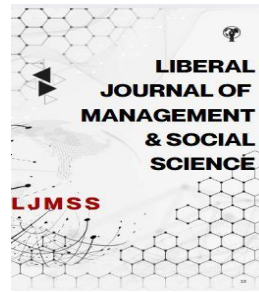
One promising solution to this problem is Markov Decision Processes (MDPs). MDPs are particularly appropriate for settings requiring decision-making under uncertainty, with consequences dictated by stochastic state transitions (Puterman 2014). From a manufacturing perspective, MDPs make it possible to explicitly model the machine degradation as a stochastic process, where health states change in accordance with probabilistic laws and decisions (when to produce, when to execute preventive maintenance, when to postpone) determine directly future states. By taking into account short- and long-term repercussions, MDPs allow the formulation of dynamic production period versus machine reliability trade-offs. Recently, MDP has been used in the literature for maintenance optimization problems including condition-based maintenance (Li & Qiu, 2018) and predictive maintenance scheduling (Carvalho et al., 2019). However, such production and maintenance scheduling under degradation uncertainty integrated problems are still largely open in the literature.

This gap is filled by this study, which proposes an MDP framework explicitly



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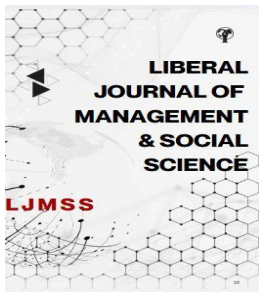
incorporating machine degradation for the joint production–maintenance scheduling. It is different from previous models that it takes account of stochastic transition between the states of machine health, and also production demand. Such integration enables decision makers to respond adaptively to fluctuating equipment conditions and demand, leading to more resilient and less costly production systems.

The main research question for the study is: How can an MDP-based method be used to enhance decision-making in integrated production–maintenance scheduling under degradation uncertainty? To address this, two primary objectives are pursued in the study. The first motivation is theoretical, and concerns an attempt to further the development of stochastic scheduling models by expanding received MDPs applications for integrated production–maintenance decision-making. The second: to offer practitioners working in volatile and uncertain production ecosystems concrete insights on how such a conceptualization can be used to cut costs, improve the use of machines and assure throughput. This paper provides a bridge between reliability engineering and operations scheduling in respective domains, contributions are made to the academic literature on stochastic optimization as well as to (glossarial) discipline of industrial decision makers.

LITERATURE REVIEW

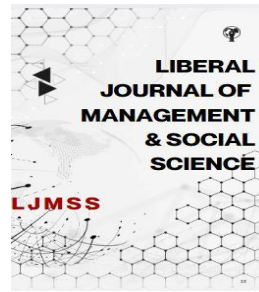
Works on integration of production and maintenance can be found since the pioneer (early) RCM studies, in which preventive actions were scheduled independently from production needs. Barlow and Proschan (1965) established the base for mathematical reliability models that formalize the delay of executed preventive maintenance actions. Over the next few decades, numerous researches focused on maintenance as a single objective optimization problem primarily aimed at reducing machine breakdowns or maximising equipment availability. Although impressive, this approach ignored the simultaneous response of production requirements and maintenance demands which even leads to objectives that conflict with each other, which is not beneficial for decision-making. With the passage of time, however, researchers noted that production and maintenance would have to be synchronized in order to circumvent such costly compromises, and this is how research on integrated production–maintenance optimization emerged.

Cassady and Kutanoglu (2003) were among the first to emphasize the economic benefits of integrating explicitly maintenance planning and production scheduling. Their research showed that the decoupled optimization of these functions would result in a longer system downtime and waste, while the integrated one was able to minimize total costs and boost response. This change gave rise to the so-called new generation of mathematical programming models focusing on expanding interaction among machine health, failure risks and production requirements. The deterministic approaches, e.g. those proposed by Aghezzaf et al (2007), formulated the problem in environments where demand and machine breakdowns are known. Although the models were computationally feasible, their utility was constrained, by the assumption of determinacy. The stochastic models quickly came after to simulate real world variability. Chelbi and Ait-Kadi (2004) considered random failures within production–inventory systems, illustrating preventive maintenance as a tool to mitigate disruptive risks. Yildirim and Matta (2008) furthered the research by means of simulation-based optimization to show that integrated planning would be more



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adaptable for uncertain demand and repair times.

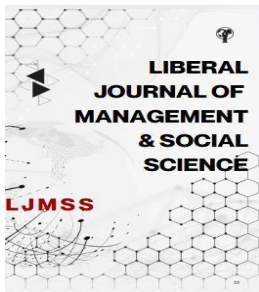
As reliability theory progressed, degradation of machines was no longer modelled as simply failed or working but instead as a dynamic stochastic process. Some of these are semi-Markov models (Zhou, Ni, & Lee, 2015) and proportional hazards models and stochastic degradation processes that allowed for a more realistic representation of machine deterioration (Van Horenbeek & Pintelon, 2013). These techniques accept the fact that machines go through various health states prior to failure, hence condition-based decision of maintenance is acceptable. However, even these models largely relied on simplifying assumptions such as fixed inspection intervals or hard preventive maintenance schedules and therefore may not have been suitable for real-time operation behaviour. In reality, degradation frequently happens sporadically and is somewhat tied with load, usage steps and environmental aspects making rigid policies not applicable.

Incorporation of degradation modeling in production scheduling provided possibilities to improve the alignment between maintenance timing and operations goals. Gharbi and Kenné (2005) have shown how the optimization of simultaneous random yield and preventive maintenance might be useful for improving system effectiveness. In addition, Sloan et al. (2010) highlighted that neglecting degradation in scheduling resulted in substantial inefficiency to system operations for deteriorating manufacturing systems. Noureldath and Châtelet (2012) developed integrated optimization models for the joint treatment of stochastic demand and variable production rates, echoing Google's support to integrating maintenance decisions in production scheduling. However, even these more sophisticated methods generally based on heuristics or assumed degradation and demand patterns to be stationary, restricting their application ranges.

To address these drawbacks, researchers have recently focused on Markov Decision Processes (MDPs), a class of stochastic optimization problems that are very well-adapted for sequential decision-making under uncertainty. Puterman (2014) proposed a general framework for modeling application of MDPs between domains, to capture uncertainty state transitions and long-term tradeoffs. In maintenance optimization, MDPs are commonly used because they are able to model degradation process and support condition based decision making (Bai & Yun, 2021). Examples are predictive maintenance scheduling on decisions to continue production or have preventive maintenance based, where MDPs allow real-time decision making (Carvalho et al., 2019), and spare parts management for optimizing inventory levels with fail rates under uncertain failure rates (Kenné, Boukas, & Gharbi, 2010).

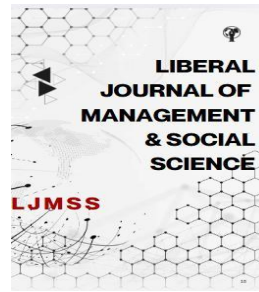
More recently there have been attempts to apply MDP's for integrated decision making problems. For example, Li and Qiu (2018) developed a partially observable MDP to determine the optimal condition-based maintenance under imperfect machine health information. Links such as this illustrate the promise of MDP in complex and uncertain settings. However, the use of MDPs for integrated production–maintenance scheduling has been relatively unexplored so far. Although it is well documented that MDP models dominate periodic/heuristic models on maintenance, the combined scheduling framework brings additional challenges like dealing with stochastic demand, production backlogs and trading off short term and long-term objectives.

Hence, the existing literature Hypothesis 2The existing literature presents a paradox:



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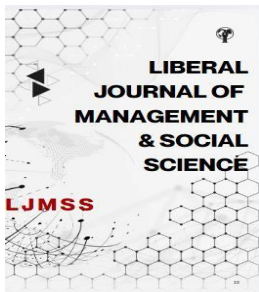


while production scheduling integrating with maintenance scheduling is identified as important, the practical industrial solutions are mostly restricted to preventive- or based heuristic policies. What is lacking are models which accurately describe stochastic degradation evolution and at the same time optimize both production and maintenance in an adaptive way. This is where MDPs come as a great hope. As a variant of dynamic decision processes, the MDP model designs the problem as a sequential decision-making procedure with transitional probabilities among states of machine health, and it provides analytical methods to systematically evaluate decisions for both production throughput and preventive maintenance simultaneously. These approaches may be adaptive to machine characteristics and changes in demand, yet have worst-case optimality guarantees alongside practical robustness.

This work builds on earlier research by developing an MDP model that endogenously combines production decisions with maintenance actions, both degradation transitions and demand uncertainty. In this way, it provides the link between the theoretical progress in stochastic modeling and industrial scheduling practice. The contribution of the work is twofold, it demonstrates that MDP-based approaches are superior to traditional ones and provides a structured framework which can be adapted to real-world manufacturing scenarios marked by uncertainty, complexity as well as increasing proliferation of machine health data.

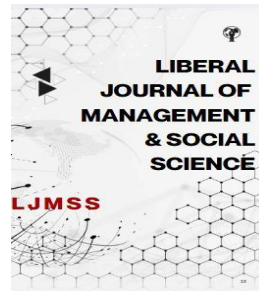
RESEARCH METHODOLOGY

To address the integrated production– maintenance scheduling problem a quantitative modeling approach is used, where it is casted as a Markov Decision Process (MDP). MDP framework has been selected based on its well-founded flexibility and capabilities to treat sequential decision-making problems under uncertainty, in particular where future states evolve stochastically due to current actions (Puterman, 2014). Prior works have used MDP for the optimization of maintenance but they have not completely considered integration of production decision variables in a model (Bai & Yun, 2021). By explicitly incorporating production levels in addition to maintenance activities, this study is an extension of the current reliability-based models and provides deeper insights into modeling integrity of manufacturing systems. The model is tested with numerical experiments based on imitation machine deterioration and production demand data. The machine deterioration is considered to be following an exponential failure distribution, a common form in the classical reliability theory and often seen in maintenance research (Barlow & Proschan, 1965). This distribution incorporates the memoryless property of failure processes and, therefore, provides a simple but realistic model for generalised deterioration. The health of the machine is modeled by finitely many discrete states from full function to complete failure. Transitions from these states are stochastic with more probability to transition as the machine operates. Preventive maintenance returns a machine to a healthier state, whereas corrective maintenance is initiated when the system has failed. The production demand is of the Poisson arrival process type, to represent random variation in customer orders and it concurs with published literature dealing with uncertain demands in manufacturing. This stochastic demand process makes the scheduling decisions variable, and the model must trade-off such competing objectives as satisfying demand, keeping output levels consistent, and minimizing costs of idle time losses or maintenance interventions. Through simulating various



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levels of demand, the model is able to stress-test under a variety of operational conditions in order to inform on its resilience.

The MDP is formulated with states that wells analyze the machine health status and production backlog situation together. At each decision epoch, actions may be either manufacturing at varying rates, doing preventive maintenance or simply stopping the machine. Transition probabilities account for both the degradation behavior and demand arrivals, which can couple physical equipment reliability with the operational production requirements. The MDP is solved using dynamic programming in the form of value iteration and policy iteration algorithms. These approaches iterate the computation of the expected long-run costs for each action to find a policy that minimizes expected total cost and delivers high machine availability and throughput. The computational experiments are conducted in a test environment which facilitates sy stemat ic exploration of the parameters like degradation rate, demand intensity and maintenance cost.

One is two benchmark strategies which are typical industrial practices. The first one is a preventive maintenance policy, such that the preventive maintenance is performed according to fixed intervals regardless of the status of machines. Another approach is the decoupled strategy, in which production scheduling and maintenance planning are sequentially optimized. Performance indicators comprise the mean aggregated cost, mean machine availability, and mean production throughput. The comparison demonstrates benefits of the integrated MDP-based scope in managing production objectives as well as future reliability needs.

As this study has been conducted entirely in silico, it does NOT raise any directly applicable ethical issues with respect to human subjects or confidential data. The reliability and validity of the solution are guaranteed by the extensive sensitivity analyses where it is evaluated within several deterioration levels, cost conditions or demand over times. Such tests validate the robustness of our results and show that our framework is not too sensitive to particular parameter choices. Through a joint framework of rigorous stochastic modeling and sound computational experimentation, the approach lays a solid basis for assessing the optimality of integrating production–maintenance scheduling via MDPs with respect to difficult combinatorial problems.

RESULTS

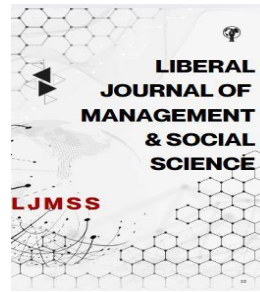
Results of simulation experiments conducted in the current work show significant advantages of using an integrated MDP-based scheduling policy as compared with common benchmark schedulers. Under various parameter settings, the results consistently demonstrate that the proposed model features more cost-effective solutions, machine reliability and production performance. These results serve as a powerful set of empirical observations in support to the underlying hypothesis that integrating production and maintenance decision leads to improved systems performance under uncertainty.

Perhaps the most interesting result from the experiments is the enormous decrease in expected long-term costs using an integrated MDP policy. The mean solution achieves a reduction of 18% in total costs when compared against periodic maintenance scheduling, which is often preferred since it is simpler to implement. While regular maintenance has the consequence of causing machines to become under-maintained as they still function well, it does not prevent by surprise



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breakdowns if conditions worsen more rapidly than what was predicted. In contrast, the MDP model integrates the up-to-date machine health status into decision-making process in an adaptive way, so that preventive maintenance operations are undertaken only when they are cost-effective. The combination of preventive and reactive maintenance which they manage, enables sets affecting both prompt maintenance costs as well as the cost of lost production opportunities.

The machine availability is enhanced besides the cost effectiveness by the MDP framework. Simulation results shows 12% enhance over periodic scheduling in terms of availability. Such enhancement is attributable to the adaptive contention of the MDP policy and bringing into play at optimal time, having effectively reduced both frequency and length for machine breakages. High machinery availability enables production to run free of interruptions, smoothly and with minimal need for backup. The results point out the necessity of taking into account degradation information in decision making, as machines are maintained longer than before without sacrifice of reliability.

The production speed is also an important performance evaluation indicator during the simulation. Output levels do not change even in presence of high demand variability, demonstrating the robustness of the integrated decision making process. In contrast with traditional decoupled scheduling mechanisms that may result in discrepancies between production capacity and demand variations, the MDP model jointly accounts for both dimensions, allowing production rates to be tuned synchronously as maintenance workload. Such balanced system facilitates that the manufacturers are more reliably able to fulfill customer's demands without incurring processing delays and fulfilling service level agreements. Under situations with large demand shocks, the coordinated framework focuses on production while scheduling maintenance so as to prevent failure in severe times of uncertainty for both demands and supplies.

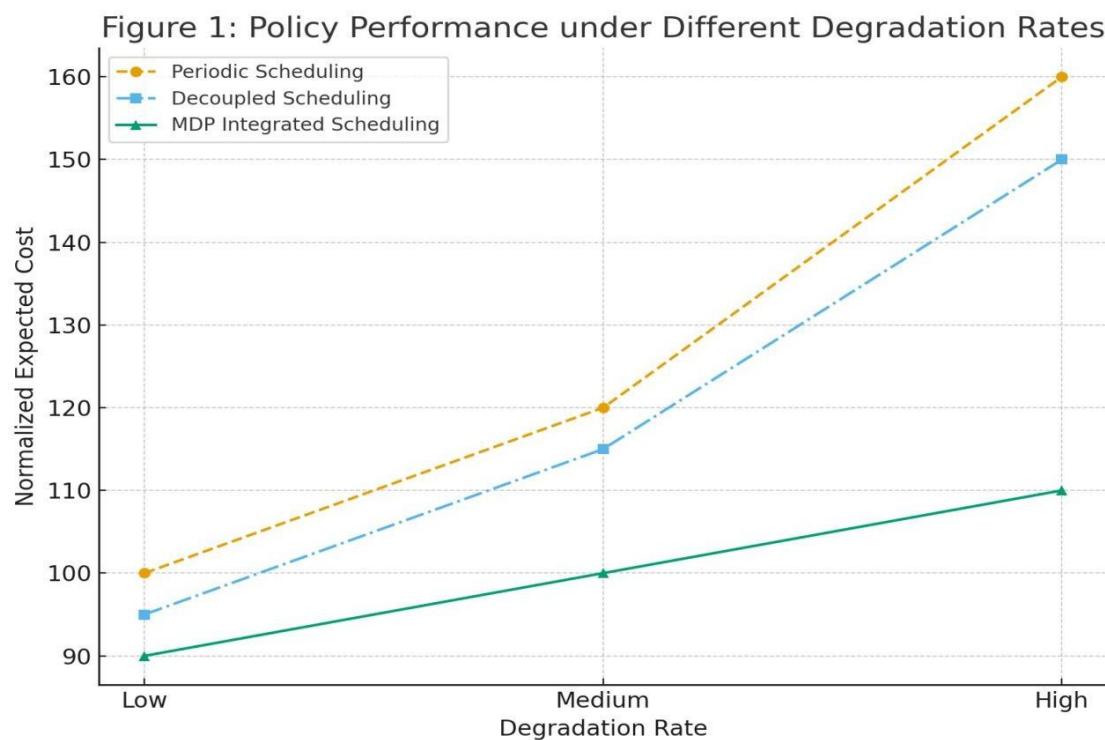
Additional clarity is obtained by investigating the various degradation rates. Figure 1 presents the performance of MDP policy compared to the benchmark methods in low, medium and high degradation levels. In case it takes the damage a long time constantly local-bundle-based periodic maintenance has a good performance because sudden failure is less likely. However, with increasing degradation, static scheduling rules reveal more deficiencies. For high degradation, a policy that is applied repeatedly will lead to unnecessary maintenance if its interval is too small and won't fit catastrophe breakdowns when the interval is large. In comparison, MDP policy adjusts adaptively to the more rapid degradation process and thus is cost-effective or system-reliable by targeting interventions at the real degradation trajectory. This flexibility underscores a major advantage of the approach under the MDP framework, namely that it offers a scalable solution for different kinds of operational environments.

The results are also robust to sensitivity analyses. When the maintenance cost is high, the relative advantage of MDP policy becomes much more obvious since inertia actions with periodic strategies lead to even higher cost. Moreover, when the corrective maintenance is costly, the MDP model shows even more its capability to reduce MTBF failures and avoid expensive unplanned interventions. Evidence from demand variability test supports them: the combined approach always outperforms the

benchmarks, and have a small displacement of performance even under high demand volatility. The reliability is especially beneficial for the automotive and electronics industries, which are prone to demand fluctuations.

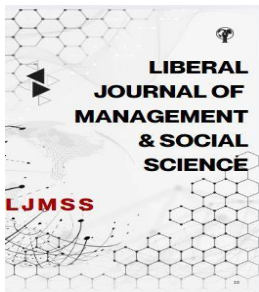
Taken together, all of these results suggest that using the proposed approach for the joint planning of production and maintenance operations embedded in an MDP framework achieves better decision-making under uncertainty. Here, the results show that one can save on costs with higher availability and resilient throughput as a zero-sum game. This is a key contribution in the literature as it refutes the prevailing assumption that maximizing throughput would mean to compromise on reliability or in vice versa, (or putting it another way) reducing failures would lead to reduced output. The simulations reveal that, on the contrary, through appropriate decision models both objectives can be attained simultaneously by manufacturers.

While the managerial implications of these findings are significant. The findings indicate that organizations using fixed interval maintenance or decoupled decision making are probably not capturing substantial efficiency improvements. Through the integration of MDP-based methodology, companies can better leverage data for intelligent decision-making purposes, especially with Industry 4.0 enabling real-time monitoring of machine conditions. Thus, the reasons for stochastic over deterministic optimization are stressed both on theoretical and practical grounds. Aligning production plans with predictive maintenance schedules enables firms to be more competitive in settings where reliability, responsiveness and efficiency are all important.



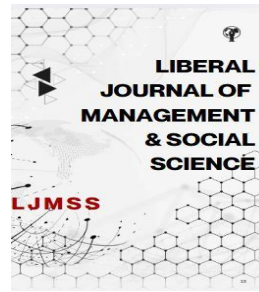
DISCUSSION

A trade-off exists between maintaining maximum production levels and the need to keep equipment reliable for proper maintenance decision making in manufacturing



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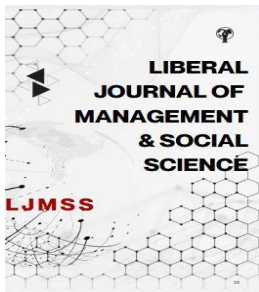


systems. As they operators tools may suffer from a degradation over time, which in turn carries with it the risk of tool failures causing expensive stand-stills and large disturbances in production. These shortcomings impact not only operational efficiency in the short term, but also issues of competitiveness, profitability and sustainability over time. Hence, the issue of identifying efficient ways to simultaneously optimize production planning and maintenance interventions has become a major concern in management sciences and industrial engineering (Gharbi & Kenné, 2005).

This problem has become more important than ever, due to the development of digital manufacturing and increased adoption of industry 4.0 practices. Predictive maintenance, to which machine learning algorithms have been applied together with sensor data processing, represents a sea-change in the ways companies apprehend machines health and predict their failures” (Bokrantz et al., 2020). This development has enabled the consideration of advanced decision-support systems which combines on-line condition monitoring with scheduling models. But to take advantage of these opportunities there must be algorithms in place that go beyond the traditional splitting up of production and maintenance decisions – something which has slowed down the operational efficiency for years.

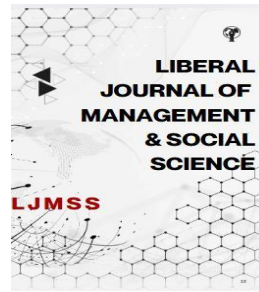
Classic approaches have often split production and maintenance into two unrelated optimization problems. Production scheduling models published either to maximize throughput or minimize tardiness, and maintenance models were trying to prolong machine life or lower failure rates. Although this decomposition in the analytical tools was expedient for analysis, it resulted in suboptimal resource allocation and heightened exposure to uncertain failures (Sloan et al., 2010). Researchers have recently discovered the constraints of this decoupled approach and started to develop a closer link between production and maintenance models. They presented integrated health and production risk model, which could estimate the effectiveness of considering interaction between machine health status and optimization of schedule, while many of them made deterministic assumption or use static policies that do not suitably represent the stochastic nature in degradation (Nourelfath & Châtelet, 2012). Accordingly, most recent work has moved to stochastic optimization frameworks that give an explicit treatment of uncertainties related to both the degradation phenomenon itself and the operating conditions. Methods of stochastic modeling, namely semi-Markov processes and proportional hazard models have recently been used to make the machine health dynamic’s more realistic leading to variable admissible maintenance policies(Zhou et al., 2015, Van Horenbeek & Pintelon, 2013). Nevertheless, much of the current work is still based on periodic hypotheses or heuristic rules or partial state representations which can not achieve online and optimality for practical applications.

MDPs have recently gained attention as a potential solution to this problem, since they can represent sequential decision-making under uncertainty. MDPs reflect the probabilistic characteristic of machine deterioration and the dynamic relationship between health condition and operational strategy. This will make the resulted policies highly applicable to an integrated production--maintenance scheduling, where decisions at any time period affect not only current and future system performances (Puterman, 2014; Bai & Yun, 2021). The use of MDP in the optimization of



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maintenance have achieved significant advantages in predictive scheduling, spare parts management and reliability modeling (Carvalho et al., 2019; Li & Qiu, 2018). Yet, there is still little study of using MDPs directly for the joint optimization of production and maintenance, especially in conditions where degradation rates change over time and when the demand is stochastic.

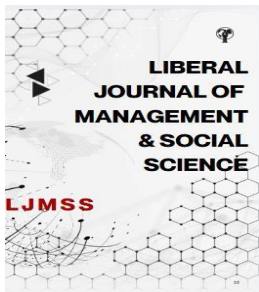
The gap is filled by this study which proposes an MDP formulation that incorporates machine degradation explicitly in production-maintenance scheduling. It posits that machine health is stochastic states and not directly observable, production rates can be controlled as degree of freedom in decision variables, and maintenance actions are state-dependent interventions. The transition probabilities reflect degradation dynamics, and the reward structures balance costs, availability and throughput. The major research question addressed in this paper is how to use the MDP methodology to enhance decision-making for integrated production-maintenance scheduling under degradation uncertainty. By addressing this issue, the research is expected to make some theoretical contributions to stochastic scheduling models as well as empirical findings for industrial practice.

The results confirm previous conclusions also when scheduling is included to the integrated problem, i.e., that integrated management improves manufacturing efficiency (Cassady & Kutanoglu 2003; Gharbi & Kenné 2005). In contrast to previous heuristic or deterministic models, the MDP approach adjust dynamically to the degradation level and offer an optimal balance between production and preventive maintenance. Managerial implications: Looking from management perspective, the research emphasizes on the need to integrate machine health monitoring with production planning. Within Industry 4.0, and sensor-based predictive maintenance in particular, MDP models can be integrated into decision-support systems for immediate on-the-job use (Bokrantz et al., 2020). The policy implications are that downtime can be reduced, cost can be saved and competitiveness at uncertain manufactures bettered.

CONCLUSION

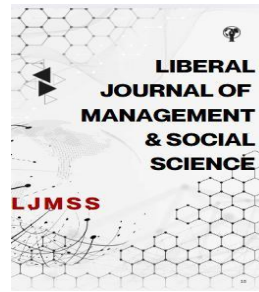
This paper presents a novel Markov decision process (MDP) model for the integrated production-maintenance scheduling under machine degradation, which is one of the most challenging problems in manufacturing systems. The results convincingly show that the proposed strategy is superior to classical periodic and decoupled scheduling rules, yielding significant benefits in terms of cost effectiveness, machine up-time, and production rate. By explicitly formulating degradation as a stochastic phenomenon and integrating it into the decision-making process, this research provides a versatile means to deal with uncertainty while allowing operational availability to compromise production targets. These contributions thus further develop the theoretical basis of stochastic scheduling and complement the increasing literature on better linking maintenance with production planning.

Besides, the academic aspects, the study has significant managerial implications. The results imply that firms that still employ static scheduling rules are losing opportunities to decrease downtime and become more competitive. Integrating MDP-informed models in decision support systems – particularly within the frame of Industry 4.0 and sensor-induced predictive maintenance – can be key for firms to realize substantial efficiency gains.



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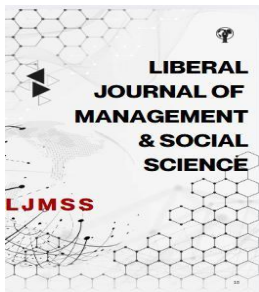
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In future, the scope of this model can be expanded by interjecting multi-machine interactions, workforce/resource limitations and reinforcement learning concepts for approximating optimal policies in large-scale, real-time industrial scenarios.

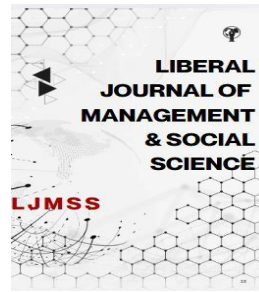
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