Advances in Reliability, Safety and Security

ESREL 2024
Collection of Extended Abstracts

An On Line Approach For Joint Optimization Of Data Driven Predictive Maintenance And Production Planning

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Keywords: smart manufacturing, data-driven PdM, production planning, joint optimization, on-line decisions

Engineering faces global transition: from predicting failures and remaining useful lifetimes (RULs) to optimizing operations and maintenance (O&M) of assets in a production system. Developments has been carried out in the field of condition monitoring and fault prediction. Next step has to be the integration of fault prediction and maintenance and repair scheduling techniques into production planning. A new framework was developed utilizing the updated RUL prognostics during the decision-making stage (Nguyen and Medjaher, 2019). Recently, plentiful research has been conducted to establish the connection between prognostics and decisions (de Pater, Reijns and Mitici, 2022; Mitici, de Pater, Barros and Zeng, 2023).

The widespread adoption of smart and intelligent devices and techniques generate vast amount of monitoring data, which help make decisions for a smart manufacturing. Smart manufacturing can be defined as making information as well as manufacturing procedures available as and when required, such that it is possible to make decisions regarding the course of any critical business operation (Petersen, 2020). Both maintenance scheduling and production planning are core factors for a smart manufacturing system. Extensive literature has focused on the joint optimization for maintenance and production planning, but few of them make full use of monitoring data.

Our aim is to establish a data-driven intelligent optimization approach which solves the real-time joint O&M decision-making problem under uncertain demand.

In this study, we consider the joint decision making on production operations and asset maintenance for a production system, considering the dynamic market demand and stochastic degradation of machines.

The production system includes a fleet of machines with the same degradation characteristics. The degradation levels of the machines determine their RULs, which are predicted based on the online degradation data. The machines can undergo preventive maintenance for a working machine in good conditions or emergency maintenance for a failed or nearly failed machine, and the maintenance restores the machines to as-good-as-new condition. A machine under maintenance is unable to make production. It takes one period to accomplish the entire procedure of maintenance including teardown and setup. The demands are predicted based on historical data and the predicted demands are regarded as deterministic input for an optimization model. The surplus items over the demand incurs the holding cost, while the unmet demand incurs the lost-sale lost. The decisions for each period, including the production plan, maintenance policy, and transaction tactics, need to be made at the beginning of a period with the aid of prediction of RULs and forecast of demands.

To solve the above-mentioned integrated optimization problem over infinite periods, a rolling horizon (RH) schema is used. The RH schema can decompose the large-scale problem into a series of subproblems with the same structure and has been successfully applied to address lot-sizing problems (Glomb, Liers and Rösel, 2022). The t-th iteration of RH considers a finite planning horizon of T periods (periods $t, t+1, \dots, t+T-1$). Adopting the RH schema, we propose an online real-time predictive maintenance and production planning (PdM&PP) approach. Figure 1 presents the outline of the proposed approach, including four interactive modules. The RUL prediction model is trained with historical database and makes online RUL prediction using the latest collected degradation data. In the demand forecast module, the demands for the coming T periods are forecasted using historical data or other information from market department. The joint optimization module establishes a mixed integer linear programming (MILP) over T periods at each iteration. The linearity in the optimization model ensures the real-time solution, which can be obtained using well-developed linear programming algorithms. In the system production module, only the O&M decisions for the current period induced from the solution are implemented. The simulation method can be developed to mimic the operations of the production system. Then, the system status changes over a period and is tallied at the end of the period.

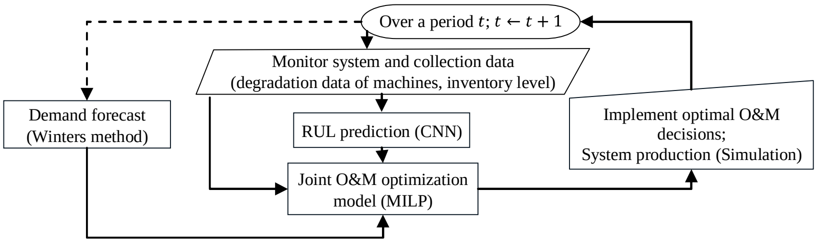

Fig. 1. Outline of the PdM&PP approach

Simulation results

To show effectiveness of the PdM&PP approach, results of four policies are compared by Monte Carlo simulation experiments. Policy 1 is induced from the PdM&PP approach with CNN as its RUL prediction model and Holt-Winters as demands forecaster. Policy 2 uses the same framework as the PdM&PP but adopts the lifetime-distribution based RUL prediction. Policy 2 does not use the online degradation data and RUL prediction. Policy 3 makes the maintenance schedule and determines the production operations seperately over the entire simulation horizon (Chen, Zhu, Shi, Lu and Jiang, 2021). Policy 4 makes the O&M decisions sythetically with the assumptiont that the true RULs and demands are known and used in the joint MILP optimiztion model. Policy 4 is the case with perfect information and is unrealistic. Figure 2 shows the simulation results, verifying the effectiveness of the PdM&PP approach. Particularly, Policy 3 performs the worst, implying that the integration of O&M decisions is superior. Policy 1 outperforms Policy 2, implying that using online degradation data is superior to the lifetime-distribution based RUL prediction that uses historical data. Policy 2 generates the results close to Policy 4, implying the goodness of the PdM&PP approach as Policy 4 is the perfect case.

Fig. 2. Comparative analysis of different polices

Acknowledgements

The first two authors were supported by the National Natural Science Foundation of China under Grant 72271226 and Grant 71971206.

References

Chen, C., Zhu, Z. H., Shi, J., Lu, N., Jiang, B. 2021. Dynamic Predictive Maintenance Scheduling Using Deep Learning Ensemble for System Health Prognostics. IEEE Sensors Journal 21(23), 26878-26891.

Glomb, L., Liers, F., Rösel, F. 2022. A rolling-horizon approach for multi-period optimization. European Journal of Operational Research, 300(1), 189-206.

Mitici, M., de Pater, I., Barros, A., Zeng, Z. 2023. Dynamic predictive maintenance for multiple components using data-driven probabilistic RUL prognostics: The case of turbofan engines. Reliability Engineering & System Safety 234, 109199.

Nguyen, K. T. P., Medjaher, K. 2019. A new dynamic predictive maintenance framework using deep learning for failure prognostics. Reliability Engineering & System Safety 188, 251-262.

de Pater, I., Reijns, A., Mitici, M. 2022. Alarm-based predictive maintenance scheduling for aircraft engines with imperfect Remaining Useful Life prognostics. Reliability Engineering & System Safety 221, 108341.

Petersen, P. 2020. 6 Examples Of Advanced Manufacturing Technology Of 2020. Retrieved from https://www.industrydirections.com/6-examples-of-advanced-manufacturing-technology-of-2020/.

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