Data-Driven Integrated Production and Maintenance Optimization

Anita Regler

Abstract We propose a data-driven integrated production and maintenance planning model, where machine breakdowns are subject to uncertainty and major sequence-dependent setup times occur. We address the uncertainty of breakdowns by considering various covariates and the combinatorial problem of sequence-dependent setup times with an asymmetric Traveling Salesman Problem (TSP) approach. The combination of the TSP with machine learning optimizes the production planning, minimizing the non-value creating time in production and thus, overall costs. A data-driven approach integrates prediction and optimization for the maintenance timing, which learns the influence of covariates cost-optimal via a mixed integer linear programming model. We compare this approach with a sequential approach, where an algorithm predicts the moment of machine failure. An extensive numerical study presents performance guarantees, the value of data incorporated into decision models, the differences between predictive and prescriptive approaches and validates the applicability in practice with a runtime analysis. We show the model contributes to cost savings of on average 30% compared to approaches not incorporating covariates and 18% compared to sequential approaches. Additionally, we present regularization of our prescriptive approach, which selects the important features, yielding lower cost in 80% of the instances.

Keywords Data-driven optimization · Traveling salesman problem · Prescriptive analytics · Condition-based maintenance · Machine learning

A. Regler (✉)
Logistics & Supply Chain Management, TUM School of Management, Technical University Munich, Munich, Germany

J. S. Neufeld et al. (eds.), *Operations Research Proceedings 2019*, Operations Research Proceedings, https://doi.org/10.1007/978-3-030-48439-2_6

1 Introduction

We consider a manufacturing environment of an one-line, multiple-product production system that faces two challenges: (i) Due to the significant differences between the products, high sequence-dependent setup times account for non-value creating downtime and (ii) the significant amount of unplanned machine breakdowns, which leads to supply shortages, lost profits and thus, customer dissatisfaction.

For an optimized production plan, the setup time and the uncertain breakdowns need to be minimized to generate more output, better utilize the capacities of the production lines and reduce the time to delivery from customer orders, leading to an improvement of customer satisfaction. In order to cope with these challenges, an integration of production and maintenance planning is needed, that does not only minimize the setup cost, but also takes into account the trade-off between breakdown costs and the additional maintenance costs, caused by frequent scheduling.

By addressing the challenge of breakdowns, predictive maintenance can, when appropriately planned, reduce machine downtime by detecting unexpected trends in feature data (e.g., sensor data), which may contain early warnings on pattern changes. Predictive maintenance can ensure the availability, reliability, and safety of the production systems. It generates profits through an undisrupted production system, optimizing cost, quality, and throughput simultaneously. However, predictive maintenance does not account for the underlying structure of the optimization problem, which might yield suboptimal production and maintenance decisions. This asks for prescriptive analytics approaches that integrate prediction and optimization.

In the course of this research we answer the following questions:

How to integrate production and maintenance scheduling for a holistic production optimization model? How can the decision maker efficiently use data of past observations of breakdowns and covariates to solve the problem? Which performance guarantees does the decision maker have and how do these scale with various problem parameters? What is the value of capturing the structure of the optimization problem when making predictions? How is the applicability of the models in practice?

2 Mathematical Formulation

This research proposes a data-driven optimization approach for integrated production and maintenance planning, where machine breakdowns are subject to uncertainty and major sequence-dependent setup times occur.

We address the uncertainty of breakdowns by considering various covariates such as sensor signals and the combinatorial problem of sequence-dependent setup times with an asymmetric TSP approach [1]. The combination of the TSP with machine learning, to simultaneously optimize the production schedule and maintenance timing, minimizes the non-value creating time in production lines and thus, the overall costs. We apply this by defining a maintenance node in the TSP graph. Furthermore, we train data-driven thresholds based on a modified proportional hazard model from condition-based maintenance. The threshold includes covariates, such as sensor data (vibration, pressure, etc.), whose impact is learned directly from data using the empirical risk minimization principle from learning theory ([2], p. 18).

Rather than conducing prediction and optimization sequentially, our data-driven approach integrates them and learns the impact of covariates cost-optimal via a mixed integer linear programming model to account for the complex structures of optimization models. We compare this approach with a sequential approach, where an algorithm predicts the moment of machine failure. The integrated prescriptive algorithm considers the costs during training, which significantly influences the decisions as the models are trained on a loss function consisting of both, maintenance and breakdown costs, whereas the predictive approach is trained on forecasting errors not incorporating any kind of costs. Our prescriptive approach is based on principles of data-driven literature, which is applied to different problems such as the Newsvendor Problem [3–5], portfolio management [6, 7], the minimization of logistics costs in retail [8] or commodity procurement [9].

To our prescriptive model the general notation (Table 1) is applied.

The parameters α and β_m are furthermore out-of-sample not decision variables, but parameters.

In order to integrate the dimension t of the covariate observations to the time used for production jobs, variables x_{ijt} and C_{ijt} have the dimension t. They are only set up in the regarding production cycle t, where maintenance is scheduled, and the job is part of the production slot. For all other t, where no maintenance is set up, the variables are set to zero. t is also used to separate and define the different production slots/cycles.

The target of the optimization models is the minimization of the costs, arising throughout the production system. Therefore, we state the following linear decision rules for x_{ijt}, y_t and z_t:

- For every $i = 1, \ldots, n, j = 2, \ldots, n$ and $t = 1, \ldots, k$, x_{ijt} is set up, whenever the edge (i, j) is in the graph and product j is scheduled after product i in production slot t.
- x_{i1t} equals one and maintenance is set up after job i for precisely one predecessor job, if z_t is set to one in t for every $i = 2, \ldots, n$ and $t = 1, \ldots, k$.
- z_t is set to one if the machine age in t plus the threshold function exceeds zero. Another interpretation is when the age is higher than the absolute value of the threshold function $\alpha + \sum_{m=1}^{l} \beta_m F_{mt}$ for every $t = 1, \ldots, k$. This is in line with the hazard function from proportional hazard models.
- y_t is set to one, whenever a breakdown occurs, and no maintenance is done in t, which accounts for a penalty setup for every $t = 1, \ldots, k$.

Table 1 Notation for the prescriptive production planning model

Sets	
$t = 1, \ldots, T$	Time frame/time steps for the sensor data. Each time frame accounts for one observation of every covariate at a certain point in time
$i, j = 1, \ldots, n$	n is the number of jobs to be scheduled. The combination (i, j) is defined as the edges between job i (predecessor) and job j (successor)
$m = 1, \ldots, M$	Set of covariates of type m
Parameters	
BM	Sufficient big number
b_t	= 1, if the machine breaks in t, 0 otherwise
a_t	Age of the machine in time frame t
c^b	Costs for one breakdown of the machine
c^p	Cost per unit time of production
c^m	Costs per maintenance setup
q_{ij}	Sum of setup and production time for j if scheduled after i
F_{mt}	Value of covariate m (numerical value of sensor observation like temperature, pressure or vibration) in time frame t
Decision Variables	
y_t	= 1, if a breakdown occurs and no maintenance is set up in t, 0 otherwise
z_t	= 1, if maintenance is set up in t, 0 otherwise
x_{ijt}	= 1, if product j is produced after job i in production cycle ending in time frame t, 0 otherwise
C_{ijt}	Completion time of job j following job i when set up in cycle ending in t
α	Intercept/feature independent term of the threshold function
β_m	Coefficient for covariate m of the threshold function

Prescriptive production planning model:

$$\min \sum\nolimits_{i=1}^{n} \sum_{j=2}^{n} \left(x_{ijt} \bullet q_{ij}\right) \bullet c^p + \sum\nolimits_{t=1}^{k} z_t \bullet c^m + \sum\nolimits_{t=1}^{k} y_t \bullet c^b \tag{1}$$

Subject to:

$$\sum\nolimits_{j=2}^{n} x_{1jt} = z_t \quad \forall t = 1, \ldots, T \tag{2}$$

$$\sum\nolimits_{j=2}^{n} x_{j1t} = z_t \quad \forall t = 1, \ldots, T \tag{3}$$

$$\sum\nolimits_{j=1}^{n} \sum\nolimits_{t=1}^{k} x_{ijt} = 1 \quad \forall i = 2, \ldots, n \tag{4}$$

$$\sum\nolimits_{j=1}^{n}\sum\nolimits_{t=1}^{k}x_{jit}=1\quad\forall i=2,\ldots,n\tag{5}$$

$$c_{1j}\bullet x_{1jt}\leq C_{1jt}\quad\forall j=2,\ldots,n;\quad t=1,\ldots,T\tag{6}$$

$$\sum\nolimits_{i=1}^{n}C_{ijt}+\sum\nolimits_{k=1}^{n}\left(q_{jk}\bullet x_{jkt}\right)\leq\sum\nolimits_{k=1}^{n}C_{jkt}\quad\forall j=2,\ldots,n;\quad t=1,\ldots,T\tag{7}$$

$$\alpha+\sum_{m=1}^{l}\beta_{m}F_{mt}+a_{t}\leq BM\bullet z_{t}\quad\forall t=1,\ldots,T\tag{8}$$

$$-a_{t}-\left(\alpha+\sum_{m=1}^{l}\beta_{m}F_{mt}\right)\leq BM\bullet(1-z_{t})\quad\forall t=1,\ldots,T\tag{9}$$

$$y_{t}\geq st_{t}-z_{t}\quad\forall t=1,\ldots,T\tag{10}$$

$$C_{ijt}\geq 0\quad\forall i,j=1,\ldots,n;\quad t=1,\ldots,T\tag{11}$$

$$x_{ijt}\in\{0,1\}\quad\forall i,j=1,\ldots,n;t=1,\ldots,T\tag{12}$$

$$y_{t},z_{t}\in\{0,1\}\quad\forall t=1,\ldots,T\tag{13}$$

The objective function (1) minimizes the overall costs. It includes the production costs c^p, the sum of the maintenance costs c^m and the sum of the breakdown costs c^b multiplied with binary setup variables. Constraints (2) and (3) set—for the t in which z_t equals one—the maintenance node (node one) to one, over the sum of all production jobs as a successor or predecessor jobs. Constraints (4) and (5) ensure, that every production job (2, …, n) is set up exactly once. The completion times C_{ijt} are calculated with the Eqs. (6) and (7). Constraints (8), (9) and (10) are the prescriptive part of the model. This part is learning in-sample the intercept and the covariate coefficients for each of the sensors and represents the decision rules out-of-sample. Constraints (8) and (9) determine the maintenance setup decision. The two constraints ensure, that maintenance is set up, whenever the threshold control constraints are reached (8). If this function is not greater than zero it is not allowed set up maintenance (9). Constraint (10) sets up the penalty/breakdown costs whenever a machine breakdown occurs, and no maintenance is done. This constraint is as well used for the learning in-sample as a penalty constraint for wrong decisions. Out-of-sample are the βs and α given as parameters and the age and the state of the machine calculated. Equation (11) sets the continuous variables C_{ijt} greater equal zero. Equations (12) and (13) are setting x_{ijt} and y_t, z_t as binary variables.

3 Results

In an extensive numerical study, we present the value of data incorporated into decision models and validate the applicability in practice with a runtime analysis. We examine the predictive and prescriptive model and compare these to a small data approach that does not incorporate covariates when optimizing a time-based threshold and the perfect foresight optimum to state cost deviations to the ex-post optimal decisions.

Not having an infinite amount of data leads in theory to a bias, as the algorithms do not have the information to determine the cost-optimal parameters. As stated by the asymptotic optimality theorem, the solution converges to the perfect foresight optimum, if given an infinite amount of data [6]. The numerical results for the finite sample bias show that our prescriptive approach tends to the perfect foresight optimum (below 1% deviation) at a considerable low amount of 1500 historical observations (predictive approach 10% deviation, small data approach 30% deviation). The challenge of the generalization error—the generalizability of the in-sample decision to out-of-sample data [3]—is most prominent with a high number of covariates and a low number of observations, causing risks for the decision maker. This is addressed with the lasso regularization extension in order to select the decision-relevant features and regulate against overfitting. This approach yields lower cost in 80% of the instances compared to the approach without regularization.

The sensitivity to the cost structure of the prescriptive model while learning is the significant difference to the predictive model. The prescriptive model adjusts the decisions according to the associated costs of breakdowns and maintenance, while the predictive model proposes the same decision regardless the costs, which leads to additional risks. This translates into cost savings of 50%, considering a ratio of 1/25 of maintenance to breakdown costs.

The overall runtimes for the training of the predictive approach (2500 observations 0.02 s) are significantly lower than of the prescriptive runtime (346 s), which shows the trade-off between runtimes and robust decisions. By considering the results of cost deviation, below 1% at a training size of 1500 with a training runtime of 18 s, the model is applicable in practice. The optimization of the sequence-dependent setup times and the scheduling of 1 month with 60 jobs on a conservative choice of machine has a runtime of less than half an hour with two maintenance setups and is therefore applicable in practice as well.

4 Conclusion and Managerial Insights

Overall, we find that the prescriptive model contributes to cost savings of on average 30% compared to approaches not incorporating covariates and 18% compared to predictive approaches. This shows the high importance of the covariates in the maintenance context, as the small data approach never captures the true nature of the machine state. Furthermore, it shows the potential in capturing the optimization problem when making predictions.

We conclude, the data-driven integrated production and maintenance optimization model is suitable to solve the challenges presented and can significantly reduce costs in the production environment.

Acknowledgement The author thanks Prof. Dr. Stefan Minner and Dr. Christian Mandl from the chair of Logistics & Supply Chain Management (Technical University Munich) for supervising the thesis and their support, as well as Richard Ranftl for sharing real-world context and technical development support.

References

1. Dantzig, G., Fulkerson, R., Johnson, S.: Solution of a large-scale travelling-salesman problem. Oper. Res. **2**(4), 363–410 (1954)
2. Vapnik, V.N.: The Nature of Statistical Learning Theory. Springer Science+Business Media, New York, NY (1995)
3. Ban, G.-Y., Rudin, C.: The big data newsvendor: practical insights from machine learning. Oper. Res. **67**(1), 90–108 (2019)
4. Beutel, A.-L., Minner, S.: Safety stock planning under causal demand forecasting. Int. J. Prod. Econ. **140**(2), 637–645 (2012)
5. Oroojlooy, A., Snyder, L., Takác, M.: Applying deep learning to the newsvendor problem. arXiv:1607.02177 (2017)
6. Ban, G.-Y., Gallien, J., Mersereau, A.: Dynamic procurement of new products with covariate information: the residual tree method. Manuf. Service Oper. Manag. (2018). Forthcoming
7. Elmachtoub, A. N., Grigas, P.: Smart "predict, then optimize". arXiv:1710.08005v2 (2017)
8. Taube, F., Minner, S.: Data-driven assignment of delivery patterns with handling effort considerations in retail. Comput. Oper. Res. **100**, 379–393 (2018)
9. Mandl, C., Minner, S.: Data-driven optimization for commodity procurement under price uncertainty. Working Paper. Technical University Munich (2019)