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Manufacturing lead time estimation with the combination of simulation and statistical learning methods

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Abstract

In the paper, a novel method is introduced for selecting tuning parameters improving accuracy and robustness for multi-model based prediction of manufacturing lead times. Prediction is made by setting up models using statistical learning methods (multivariate regression); trained, validated and tested on log data gathered by manufacturing execution systems (MES). Relevant features, i.e., the predictors most contributing to the response, are selected from a wider range of system parameters.
The proposed method is tested on data provided by a discrete event simulation model (as a part of a simulation-based prediction framework) of a small-sized flow-shop system. Accordingly, log data are generated by simulation experiments, substituting the function of a MES system, while considering several different system settings (e.g., job arrival rate, test rejection rate).
By inserting the prediction models into a simulation-based decision support system, prospective simulations anticipating near-future deviations and/or disturbances, could be supported. Consequently, simulation could be applied for reactive, disturbance-handling purposes, and, moreover, for training the prediction models.

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Keywords: Lead time, Simulation, Robust prediction, Statistical learning

1. Introduction

Make to order production requires a proper estimation of manufacturing job lead times (LT) when dealing with production orders. Moreover, a reliable forecast on systems' load and output is also mandatory both for due-date quotation as well as for production control decisions. Since LT estimation is a difficult task, resulting in often unreliable output (e.g., when applying well-known shop-floor related characteristics and calculation methods as for instance combining total work content of the jobs and actual WIP), novel methods, considering a bigger set of system parameters influencing the LT are required. Though, discrete event simulation is well known and widely applied for predicting future systems' conditions, analytical interpretation of simulation outputs as prediction models would foster decision making on tactical level of production planning and control.

Simulation technologies are often used in supporting production control decisions and this is also particular for large-scale manufacturing systems. Several different applications of discrete-event simulation models in control of manufacturing systems were presented in [1] and [2].

A discrete-event simulator developed for the daily prediction of work in process (WIP) position in an operational wafer fabrication factory to support tactical decision-making is described in [3]. The model parameters are automatically updated by using statistical analyses performed on the historical event logs generated by the factory. A simulation study is presented in [4] which is applied to compare alternative WIP management policies, while [5] introduces a model, quantifying the effects of lot size changes, lot release controls and machine dispatching rules, on selected Key Performance Indicators (KPI-s) (throughput, process time and process time spread) for manufacturing steps. A simulation-based scheduling framework is presented in [6] for handling

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disturbances and creating updated schedules in reaction to the unpredicted situations, by combining both single criterion dispatching rules, and adjustable multiple-criteria decision making techniques. LT estimation methods are given in [7], estimating parameters of a regression model applied on shop simulation models.

Consequently, the main challenge is the constant availability of the prediction models, which, this way requires a periodic review and training, obviously, provided by simulation systems.

Accordingly, the structure of the paper is the following. In Chapter 2 the combination of discrete-event simulation and statistical learning methods is presented, focusing on the proposed simulation-based prediction framework and the statistical learning methods required by the framework. Chapter 3 introduces a set of comprehensive computational experiments by introducing a test production system and the implemented statistical learning models in order to provide explorative analysis of the system, as well as prediction on manufacturing lead time of jobs. Finally, conclusions are drawn and future work is described in Chapter 4.

2. Combination of simulation and statistical learning

2.1. Proposed simulation-based prediction framework

The main goal of the framework introduced here is to provide a self-building production simulation, capable of both prospective (e.g. locate anticipated disturbances, identify trends of designated performance measures), and retrospective (e.g. gathering statistics on resources) simulation functionalities. Self-building simulation means that the simulation model is built up by means of the combination of the MES data as well as the knowledge extracted from the MES data (e.g. resource and execution model). In addition to the automatic model building feature, main requirement of the solution is to minimize the response time of the experiments and to enable the quasi "real-time" applicability of the simulation [8],[9].

Regarding the main operation modes of the simulator in the proposed architecture (Fig 1) are as follows:

- Off-line validation, sensitivity analysis and statistical modelling of the system. Evaluation of the robustness of the system against uncertainties (e.g., different control settings, thresholds and system load levels). Consequently, this scenario analysis might point out the resources or settings which can endanger the normal operation conditions. In Fig 1 Off-line simulation represents the comprehensive model of the plant.
- On-line, anticipatory recognition of deviations from the planned operation conditions by running the simulation parallel to the plant activities; and by using a look ahead function, support of situation recognition (proactive operation mode, Fig 1).
- On-line analysis of the possible actions and minimization of the losses after a disturbance already occurred (reactive operation mode, Fig 1), e.g., what-if scenario analysis.

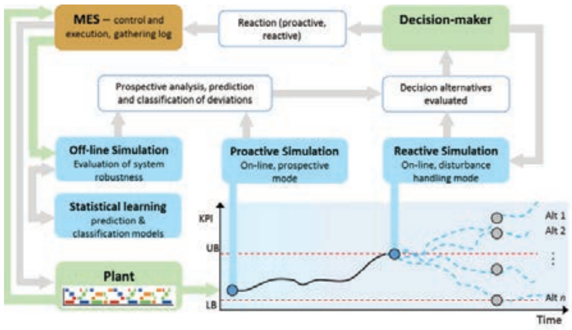

Fig 1. Plant-level active disturbance handling realized by using statistical learning methods and reactive/proactive operation modes for simulation.

In Fig 1, Plant represents the underlying production system, which is generally controlled through the manufacturing execution system (MES). Thus, green arrows represent production related data provided by the plant (e.g., resource status, job completion, or, the performance measure KPI of interest in the current case), either gathered by the MES and stored as log data, or, monitored on-line by, i.e., the simulation framework. Contrary, grey arrows represent an interaction or information exchange, e.g., the Decision-maker might control the process of the production (highlighted as Reaction) of the plant by the MES system.

In a real-world application, the three main distinct operation modes follow each other during operation.

In contrast to the on-line proactive mode of the simulation, in the off-line scenario, simulation is applied in combination with the MES log data for setting up and parameterizing statistical learning prediction models (Statistical learning, Prediction and classification models in Fig 1). Once the prediction models have been set up as result of the off-line analysis, permanent, on-line simulation analysis of the manufacturing system is performed (highlighted by Time in the bottom right corner of Fig 1). This means a rolling horizon monitoring of the productions systems' behaviour (e.g. by monitoring preselected performance measure of interest, e.g. LT of jobs) in advance by using prospective simulations. In case of a relevant deviation occurs, i.e., a situation is recognized which might endanger the production, a prospective analysis and classification of the deviations are performed. At this point the models obtained in the previous, off-line mode are combined with the actual simulation results in order to analyse the possible effect of the deviation, and moreover, to filter out unnecessary interventions. For instance, in Fig 1 LT is expected to be out of the range defined by lower (LB) and upper (UB) bounds. Consequently, reactive simulation mode is initiated, where a predefined set of possible solutions (Decision alternative *1* – Decision alternative *n*, denoted as, e.g., *Alt 1*) for normalizing the production is preformed, highlighted as disturbance handling mode in Fig 1.

The simulation model structure in the simulator is the same for the three operation modes, however, the granulation (level of modelling detail), time horizon, applied failure models and considered outputs depend on the purpose of the experiments

[8]. In the on-line modes the simulation models represent the virtual mirror of the plant and run parallel to the real manufacturing environment, instantly simulating the future processes for a predefined short period.

In the paper, the off-line operation mode of the simulation and the prediction models are focused on. Interested readers might refer to [10], where on-line application of the simulation framework is introduced more in the details.

2.2. Prediction models for production control decisions

In order to extend the capabilities of the simulation towards prediction and estimation of future scenarios' results, the use of statistical learning models are proposed.

Basically, statistical learning refers to a set of methods for understanding and learning from data and providing solutions to understand the correlations among parameters and processes [11]. There are two main classes of these tools: the supervised and unsupervised learning techniques. Supervised learning aims at predicting some output parameters based on the input parameters and the priori known training set. The most fundamental supervised learning methods are the linear regression models capable of predicting a value of a quantitative output variable, assuming that there is approximately a linear relationship among the input/output variables. Other effective but simple techniques for practical applications are the tree-based methods that can be used both for regression and classification as well. The general idea behind these methods is the partition of the feature space into a set of disjoint rectangular regions, and fit a simple model in each one [11]. Building a regression tree over a given dataset is composed of two general steps. First, the feature space is divided into a set of disjoint regions, then for every observation which falls into a certain region the same prediction is made that is the mean of the region.

By building regression models over simulation data, one can estimate the production parameters even besides a dynamic environment. Tree-based models (e.g., random forests) are applied for estimating the capacity requirements of modular reconfigurable system by utilizing the results of several simulation runs in [12], while in [7], a tree construction approach is introduced for lead time estimation.

Regarding the simulation-related applications, regression and prediction models can be built over simulation-related data to support simulation-based optimization methods, in which some of the objective function or constraint(s) are represented by functions that are approximated by using the results of simulations [13]. The reason for applying simulation in these cases are usually the computational complexity or the lack of analytical expression of the objective function and/or constraints. These challenges are often faced when stochastic functions have to be represented in the optimization models [14]. A more general description of the input and output parameters of simulation models' is given by meta-models that are aimed at approximating the behaviour of system with mathematical functions [15]. In [16] regression models are introduced on simulation data to analyse the functional relationship among dispatching rules, due-date assignments and shop-load ration in job shops. Similar approach is applied for a dynamic job-shop, however, simulation in this case was applied for evaluation only [17]. In [18], a multiple regression analysis platform was introduced, that enables prediction of different future scenarios considering the actual conditions of the production system.

It is assumed that by inserting the prediction models into the proposed simulation-based decision support system, prospective simulations anticipating near-future deviations and/or disturbances, could be more effectively supported. Consequently, simulation could be applied both for proactive and reactive, disturbance-handling purposes, and, moreover, for (off-line) training the prediction models.

3. Computational experiments

3.1. Description of the production system to be examined

The proposed method was tested on data provided by a discrete event simulation model of a small-sized parallel flow-shop system (Fig 2). Accordingly, log data are generated by simulation experiments, substituting the function of a MES system, while considering several different system settings (e.g., job arrival rate, test rejection rate). In each case a job is finished on a machine the actual status of the entire system is logged (timestamp, product type, location, WIP, buffer levels, etc.), considering information available in a real system.

The test production environment consists of five processing units (machines, grouped as stage 1 and stage 2) each with a buffer in front and a testing machine (stage 3) on which each product has to be tested (Fig 2). If this test is failed and the product is rejected, it is sent back to stage 2. Each job has a certain product type (A, B or C) assigned upon entering the system with equal probability and has to complete a process at each stage. There are two different levels of system load to be investigated, thus mean inter-arrival time (t_a) of the jobs is 260 for a high and 295 seconds for a low system load, while no job collection or delay is applied. Routings are set dynamically, i.e., after entering the system or finishing processing on a machine the next machine is selected with the shortest input queue. Processing times are collected in Table 1. It is obvious that the processing times are product-type dependent at a selected stage, meanwhile the testing procedure may vary within a predefined time range (lower and upper bound), independently from the type of the job. Jobs are pulled to the machines from the input buffers by using the FCFS rule.

No setup times are considered in this model and the machines have a 90% availability during the production, but different mean times to repair (MTTR, Table 1).

Fig 2. The layout and material flow of the test system.

Table 1. The main characteristics and parameters of the test production system.

		Stage 1 machines			Stage 2 machines		Stage 3 testing	
		SP0	SP1	SP2	SP3	SP4	SPT LB	SPT UB
	Type A	12 (0.0)	12 (0.0)	12 (0.1)	6 (0.0)	6 (0.0)	2:50 (0.1)	3:30 (0.1)
Processing time [min] (systematic fail ratio or reject rate)	Type B	16 (0.1)	16 (0.0)	16 (0.1)	8 (0.0)	8 (0.0)	2:50 (0.1)	3:30 (0.1)
	Type C	10 (0.1)	10 (0.0)	10 (0.0)	3 (0.0)	3 (0.0)	2:50 (0.1)	3:30 (0.1)
Availability [%]		90	90	90	90	90	90	
MTTR [min]		10	10	10	20	20	10	

An important part of the experiments is to include some, so called, systematic failures during the processing of the jobs. It means that at a certain constellation (e.g. Type A on machine SP2) a certain probability is assigned for failing the process (e.g., the product type is difficult to assemble and the machine or operator usually makes errors). This does not influence the processing time, but the outcome of the testing process at stage 3. Consequently, in parallel to the normal reject rate (last two columns in Table 1), there are some jobs having a "systematic fail" built in, which will be recognized during the testing. After rework, jobs must be processed (reassembled) on stage 2 and tested again.

Thus, an expected total work content (TWK), indicating a minimal lead time, of each product types are the sum of the mean processing times along the manufacturing process (mean set-up time is zero while batch size equals 1): 1270, 1630 and 970 seconds, for type A, B and C, respectively.

The above detailed settings of the production systems resulted in a relatively high average machine utilization level on stage1 machines, 90 and for the testing machine at stage 3, 85. Stage 2 machine utilization was around 75 percent.

Moreover, by using the workload formula given in [19], the expected overall utilization level of the test system is 83% (without reject and rework). These levels could be considered as a proper level for lead time estimations [7], since, representing a real-world problem, there will be several jobs waiting in the system, making lead time estimation challenging, but, parallel keeping the expected WIP level manageable (e.g., by using Little's law formula [19], the expected WIP is approx. 32 jobs). Note that as the utilization level (and system load) increases the estimation of the job lead times getting more difficult and unstable [7]. In Fig 3 the main characteristics of the job execution on the simulated test system are highlighted.

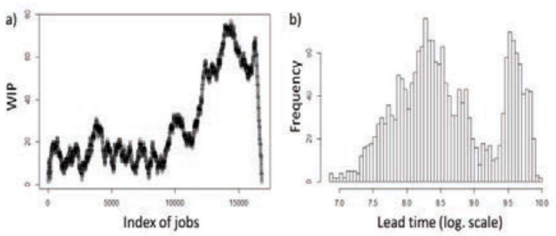

Fig 3. Main characteristics of a simulated execution of 2000 jobs in the test system for a lower system load level. a) Logged WIP level; b) Histogram of the job lead times on a logarithmic scale.

As the result of 2000 jobs going through the system the fluctuating WIP level (Fig 3a) and the histogram of the job lead times (Fig 3b, on a logarithmic scale) are given. It is obvious that the bimodal distribution of log-lead times are a consequence of the two distinct levels of WIP (before and after index 10000).

3.2. *Selection* of prediction parameters

The proposed statistical learning methods, introduced in Section 2.2 were applied on the historical log data provided by the simulation experiments, outlined previously. This section introduces first the feature selection applied in order to have the relevant parameters left in the models only. Then, two particular analysis are explained in details: 1) giving an explorative analysis, focusing on structure exploration (finding hidden failures); 2) applying prediction models for lead time estimation for different system conditions.

Once the test systems parameters are tuned in order to have a mostly stable and steady behaviour thorough the time horizon of the experiments in the simulation, the next step is to prepare the data for model formulation and estimation.

As it was stated before, collecting logs means that in each case a job is finished on a machine (or tested or event sent for rework) in the simulation system the actual status of the main parameter of the system is logged in a record of a log file (Table 2).

Here the main goal is to have particular entries in one line of the table containing all the relevant features (input variables) might describe the resulted outcome (output, or response variable) of the experiment (also referred to as observation). Therefore, log data must be preprocessed to be able to formulate the feature table (Table 3), necessary for model training and validation.

Table 2. Initial parameter set available from the log files

parameter	description
ID	Job ID
time_OUT	time stamp of when the process was finished
Location	machine ID, where process of the job was finished
rework	if the process was a rework
type	type of the job (product)
FailRate	1- the actual fail rate of the testing process (quality)
WIP	number of jobs in the system
Buffer levels	jobs waiting to be processed in the different queues

Table 3. Excerpt of a resulted feature table, aggregated to include relevant features describing jobs' behavior passing through the system.

ID	SP0	SP1	SP2	LT	type	FRate	WIP	B	…
1	1	0	0	1262	A	0.00	1	1	…
2	1	0	0	3335	C	1.00	7	1	…
3	1	0	0	4892	B	0.89	22	4	…
4	1	0	0	6769	A	0.92	20	6	…
5	0	1	0	4017	A	0.92	20	5	…

Routing of the jobs, as one of the major influencing factors, are assigned dynamically, but, however, can be tracked by the log entries (using *Location, ID* and *Type*). That means in the current representation, assigning a level one value to the certain machine (*SP0, SP1* or *SP2*) on which the job was processed at Stage 1. Other sections of the routing are irrelevant, thus are not mapped.

Similarly, job lead times are calculated from the logs (*LT* in Table 3) and assigned to the jobs by using the *time_OUT* time stamps (Table 2). It was assumed that WIP level strongly influences LT in the system examined, thus, WIP and certain buffer levels (number of jobs waiting to be processed) in front of the machines are added to the feature table (*B, B2, … , B12* in Table 3) as well.

Preliminary analysis of the features are given in Fig 4 in form of a correlation matrix of the selected variables. Note that the variable *type* is removed from this analysis, as it is a categorical variable [11]. As it was expected, the response variable LT (*lead* in Fig 4) is highly correlated with the features describing the system load (*WIP* and buffer levels).

3.3. Explorative analysis

After retrieving the feature table and all the log data from the simulation experiments, it is obvious to provide an explorative analysis, focusing on structure exploration, i.e., finding hidden relations resulting diverse response of certain inputs. In our case it means that (as introduced in Section 3.1) for some particular routing and job type combinations the probability to fail the test at Stage 3 will be above the "normal" rejection rate. It is presumed that the LT-s must reflect these constellations.

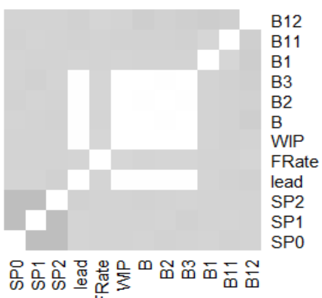

Fig 4. Graphical representation of the correlation matrix of the parameters in the feature table. White is a high positive, while dark grey is a negative correlation.

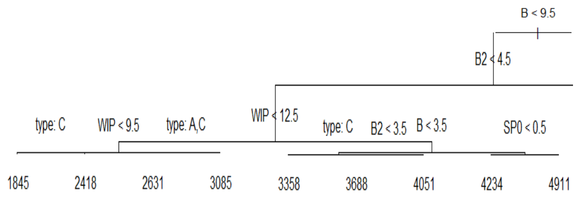

Fig 5. Prediction tree on the training set (excerpt).

However, in the current experiments introduced here these issues are known in advance, but in a real-world situation a structure exploration might be unique for identifying these underlying relationships.

In order to test the outcome of the predictions, first available data of the experiments were split into training and testing sets (one half each). A regression tree (

Fig 5, the left part is shown) was built by using the training set data only, but all the features available (general setting for the smallest allowed node size = 100). It can be seen that for low system load situations the shortest lead time (1845) is assigned to job type C (in accordance with the expected TWK). In contrast, e.g., if the WIP is above 12, the LT for a job type B is either 4234 or 4911 if in the routing SP0 station was affected or not, respectively. Tree pruning was applied, and a new tree had been created in order to avoid over-fitting the model [11]. This is a systematic K-fold cross validation process to find the deviance or number of misclassifications as a function of the cost-complexity parameter [20]. In this new tree input variables used in the tree construction had been reduced, i.e., *B, B2 WIP* and *SP2* were predictors with relevance.

3.4. Prediction on the test set

As the number of leaves (distinct and non-overlapping regions) in the tree are strongly limited, the prediction power of this model is expected to be low. The mean squared error (MSE) provided by the model when predicting from the test set was 952. Since it is apparent that the resulted tree based prediction model is useful for structure exploration as it was shown before, however, applying it for predicting LT, as the original goal, requires the application of other prediction models making comparison possible. Therefore, two other models, introduced in Section 2.2, were constructed on the training set. A multiple linear regression was formulated based on the strong correlation of system load related variables and the response variable LT. The general linear model resulted in the coefficients, where the higher intercept coefficient (3582) is compensated by the *FRate* (-3079). Regarding model quality, the R^2 value, showing the variance described by the model, is 0.975, while the MSE, calculated on the test set by the model, is 816.90, significantly lower compared to the previous tree based model.

Finally, an extension of the tree based method, a random forest model was constructed on the training data. This means that a number of decision trees are created on bootstrapped training samples [11] in order to try to reduce high

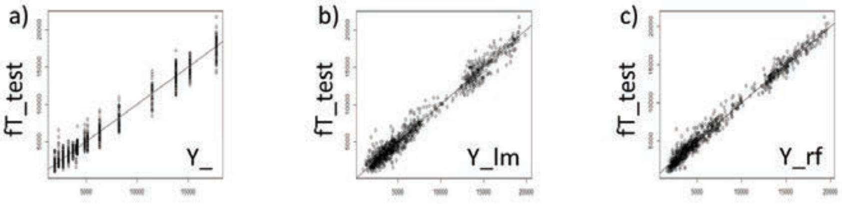

Fig 6. The function of model predictions (Y_) and test set values (fT.test) for the (a) prediction tree, (b) linear and (c) random forest models.

model variance. Building these decision trees, each time a split in a tree is considered, a random sample of *m* predictor variables is chosen as split candidates from the full set of *p* predictors. The split is allowed to use only one of those *m* predictors. This method is mostly helpful when dealing with a high number of correlated predictors. As expected, the quality of the prediction by applying this model on the test set, using 500 trees, is the best, compared to the other two solutions. MSE is 652.8 and R^2 value is 0.98.

In Fig 6 the comparison of the prediction performance of the three models are highlighted. It can be seen that the prediction and test set values are the closest for the random forest model (values are close to the solid line representing a perfect prediction match) within the whole range of predicted LT values (*Y_*). Contrary, the simple decision tree model provides a limited number of predicted values, thus in several cases the real output is away from the predicted one.

4. Conclusions and future work

In the paper, a novel method was introduced for multi-model based prediction of manufacturing lead times. By inserting the prediction models into the proposed simulation-based decision support system, prospective simulations anticipating near-future deviations can be supported.

Future work covers testing the prediction models capabilities against changing, volatile system parameters. The degradation of the prediction power is expected, thus, however, a simulation supported re-training will be examined. This is important for the random forest model, which is highly sensitive for predictors taking values out of the expected boundaries (e.g., unexpected WIP level). However, the predictor variables are selected from a wider range of system parameters, applying systematic model selection methods would be a desirable way for improving model accuracy. Current results are to be compared to state-of-the-art analytical prediction solutions available in the literature.

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