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# Knowledge-based process planning for economical re-scheduling in production control

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**Abstract**

Nowadays, high flexibility and responsiveness towards capacity adjustments are key to successful production planning and control in manufacturing. Moreover, many companies – especially job shops – have to deal with short-term re-scheduling. This article presents an approach for knowledge-based process planning to enable an economic evaluation of re-scheduling in the manufacturing system. For that purpose, the manufacturing costs for each workpiece are calculated based on determined parameter sets and process time under consideration of potential capacity adjustments. The knowledge-based process planning is necessary to derive reliable process times for re-scheduling and cost calculating. Hence, a pre-study is carried out to define flexible machine learning algorithms for knowledge-based process planning.



*Keywords:* adaptive manufacturing; machine learning; knowledge based system; scheduling

## 1. Introduction

Today's production – especially in job shops – is characterized by machine-related planning of process parameters, program codes and work schedules. The assignment of machines to work steps depends on the production time and the process parameters. However, due to unexpected disturbances in the operational workflow, it may become necessary to re-schedule existing work [1, 2]. To avoid economic losses, work steps must be re-scheduled quickly and efficiently to find the best alternative to the planned machine. Therefore, it is necessary to develop a method that automatically re-schedules production orders to possible alternative machines. However, it is essential to know the respective process times in order to re-schedule the production successfully to achieve a robust scheduling, which is a main challenge for cyber physical production systems [3]. Moreover, despite any changes of machines and process parameters, the required workpiece quality must be maintained. For that purpose, the proposed approach considers a knowledge-based planning of process parameter, which allows calculating production times of alternative processes parameter. Since the results must be available within a determined period of time, knowledge-based process planning should be conducted automatically.

The paper is divided into two parts. In the first part, a brief introduction about the superordinate approach of economical re-scheduling of manufacturing orders is given. In the second part, a method is introduced and investigated that derives process parameters for turning operations based on data analysis. Hence, process times as a major input variable for the re-scheduling can be calculated.

### 1.1. Economical re-scheduling

The economical re-scheduling approach is based on the dynamic bid price algorithm by Denkena et al. [4], who considered a relation between cost and capacity. The approach of economical re-scheduling can be assigned to different levels of the automation pyramid [5], as shown in Fig. 1.


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The approach links the levels of business (ERP), operations and control (MES), process control (SCADA) and the field network (machine). At the beginning, work preparation deploys a work schedule by defining a workstation/machine, equipment and process parameters, e.g. by using Computer Aided Manufacturing (CAM). If the production schedule can be carried out as planned, it is assumed that by choosing the most efficient machine the highest economic benefit will be achieved. In case of a machine breakdown or rush orders, the production schedule must be changed quickly. Compared to the classification of the cyber physical production system architecture [6, 7], the approach is based to the cognition level by using decision support to select the best alternative. Another approach is to use alternative production routes and determine the most efficient alternative work schedule for this purpose [2]. Other approaches focusing on integrated process planning and scheduling [8]. As shown in Fig. 1, the re-scheduling procedure is triggered by an event, e.g. a machine breakdown. The re-scheduling method contains four models:

- Customer classification model
- Schedule and capacity model
- Cost model
- Knowledge-based process planning

The customer classification model separates the business customers according to their economic importance to the company. Feasible production times are calculated from the process parameters, which are derived from the knowledge-based process planning. Within the schedule and capacity model, it is checked whether the dates of delivery of all orders are in time or not. The cost model uses the re-scheduled work schedules to calculate resulting production costs by considering capacity adjustments and the approximated production time from the knowledge-based process planning. Within the scope of a preliminary calculation, the cost price can be determined by taking machine hour rates, labor costs and the contract penalties for order postponements into account [4].

However, each model relies on different data, depending on its level within the automation pyramid. A major challenge in economic re-scheduling are reliable process data in work schedules, primarily the approximated production times. Because needed information as process parameter and production time vary strongly depending on the machine. The method of knowledge-based process planning allows the calculation of approximated process times for feasible sets of process parameter. This enables economical re-scheduling. Transfer times for material, parts and tools are not taken into account.

### 1.2. Knowledge-based process planning

Detailed process planning is part of work preparation and defines feasible process parameters of process control variables (e.g. feed or cutting speed). Despite recent developments in the field of machine data acquisition and analysis, detailed process planning, especially for turning processes, is often carried out manually based on the experience of the machine operator. This reduces the flexibility of the production due to the dependence on experienced personnel. In addition, the overall process knowledge of the company is not fully exploited due to different machine operators as well as limited documentation of the processes. A knowledge-based planning of process parameters could help to overcome these problems and ensure the selection of suitable process parameters even when production orders are re-scheduled on short notice. In the following section, a brief literature review of knowledge-based process planning is given. Subsequently, a novel approach is presented and evaluated in a case study.

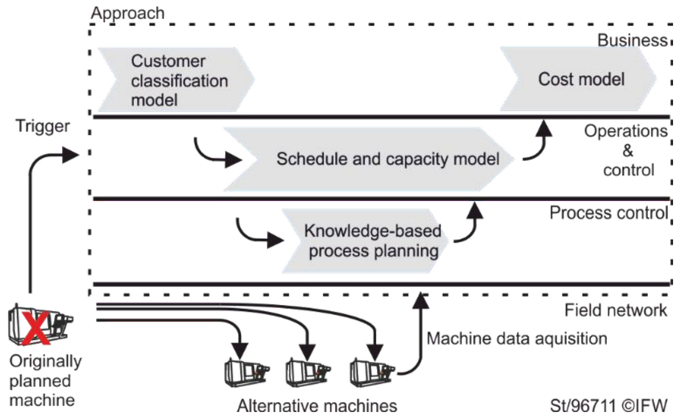


Fig. 1: Approach of economical re-scheduling in production control under consideration of resource utilization and machine tool capabilities.

## 2. State of the art of knowledge-based process planning

Detailed process planning is the last step in work preparation before the start of production and followed by production control [9]. Since the choice of process parameters depends strongly on machine tool characteristics, re-scheduling requires a revision of the selected process parameters [2]. For the subsequent data analysis, the use of machine learning methods is investigated in addition to existing planning methods. An approach considering data mining can be found at Große Böckmann et al. [10]. Especially for knowledge-based detailed planning of the turning process, the most frequently used variables are the basic cutting parameters feed (f), cutting speed ($v_c$) and depth of cut ($a_p$). In many cases, the predicted target value is the surface roughness (Rz). Davim uses a feedforward artificial neural network to predict the surface roughness depending on the cutting parameters [11]. Asiltürk considered surface roughness, but applies an artificial neural network with backpropagation and multiple regression [12]. Kant correlates the surface roughness with the tool wear to assume energy consumption in turning, by using grey relational analyses [13]. Moreover, grey relational analysis was also applied to the turning process in order to optimize process parameters with regard to the targeted surface roughness. Further, the response surface method has also attracted attention for the turning process [14]. In addition, the selection of the optimum tool geometry with the variables cutting edge rounding, setting angle and angle of chamfer was tested using the response surface method [15]. Gupta is taking more target variables into account (surface roughness, tool wear and cutting force) by using a response surface methodology compared with a particle swarm optimization [16]. Furthermore, Senthilkumar predicts the expected wear of the tool depending on the cutting

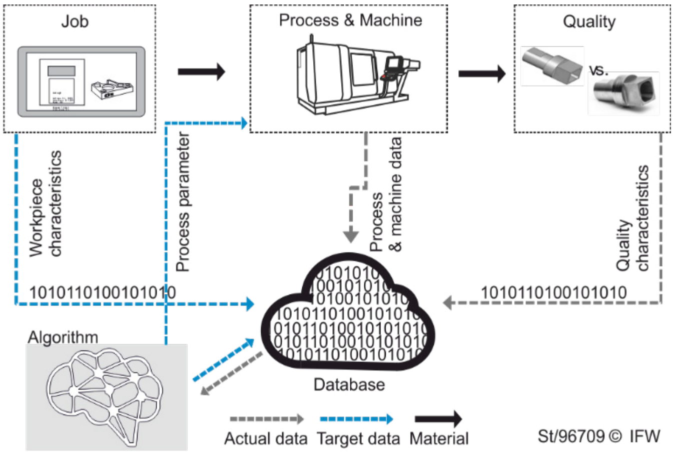


Fig. 2: Data stream of knowledge-based process planning.

parameters feed, cutting speed and cutting depth and workpiece material to optimize the parameter sets by a non-dominated sorting genetic algorithm [17]. Besides, the gradient boosted trees have been already applied for allocation problems [18], but not for detailed process planning.

In summary, many approaches aim at a better determination of the parameters of the process control variables. The most addressed process variables are surface roughness and tool wear. The basic idea of these approaches is a largely automated use of experience knowledge to predict several target values within a company. However, the existing approaches are limited with respect to the database or the analyzed process variables. For example, only an optimized selection of the tool takes place or the required basis of recorded data is too low. Within the approaches in the literature, commonly a mathematical description of the behavior of one process output variable (e.g. tool wear) is given. Some approaches take parameter optimization into account [14 - 17]. Certainly, no parameter sets are predicted for a defined surface roughness. The approaches lack a superordinate approach, which combines detailed process planning and production control.

## 3. Approach of knowledge-based process planning

Knowledge-based process planning requires data along the digital backbone of the enterprise. As depicted in Fig. 2, several data sources are necessary. Data to be entered manually, such as the measured surface roughness or the target roughness from a technical drawing must be processed via applications. This allows the respective information to be transferred to an SQL database. Based on Fig. 3, the approach performs three main functions:

1. Updating the tool database
2. Determining reliable data for process planning for explicit orders
3. Enrichment of the database with the measured roughness in order to make better prediction for the second function

With respect to the knowledge discovery in databases process [19], the task of process planning can be divided into three sections: data selection, target parameter optimization and target parameter recommendation. As shown in Fig. 3, each section includes different data sets, filters and calculations.

### 3.1. Selection

In the first section, the job data is analyzed to identify whether an identical workpiece has been machined in the past. This contains workpiece geometry and material, as well as information concerning the requirements. The first step is to check whether the available historical information already contain data points that correspond to the order workpiece (with regard to geometry and material) and meet the placed requirements (with regard to surface roughness). In this case, repetition planning occurs. Otherwise, a rule-based data collection takes place to select data points suitable for similarity planning. Subsequently, it is checked whether sufficient data points are available for a similarity planning. If there is not a sufficient number of data points, a manual re-planning takes place. However, this case is not the subject of this paper. If sufficient data points are available, similarity planning takes place in the form of manipulated variable optimization.

### 3.2. Optimization

The section of optimization includes process modelling to estimate the result of the machining process in terms of quality using tool data, material data and limiting conditions, e.g. machine capabilities. The process model is developed by a machine learning algorithm combined with a metaheuristic, to derive several sets of optimized process parameters. The optimization of the target variable value starts with the determination of the number of cuts. For this purpose, historical data is filtered according to workpieces whose depth of the feature (distance between raw material and final shape) is at least as high as the depth of the feature to be produced from the order data. The number of cuts of the workpiece from the historical information is then determined as the number of cuts which has delivered the best target values. Next, the historical data is transformed and the initialization of the starting point of the metaheuristics (e.g. different combinations of process control parameter). This is done by generating parameter combinations by a particle swam optimization within defined limits, which are determined by the limiting conditions of the manufacturing process and the machine capabilities. In addition, with regard to the recommendation of a feasible tool, it is ensured that every available tool geometry is taken into account in the metaheuristic. This is achieved by including all available tool geometries in the tool database. When optimizing the process parameters, it is initially assumed that the tools are not subject to wear.

The process parameters generated by the particle swarm optimization are used as input variables for the process model to predict the target values (e.g. a specific surface roughness). The particle swarm optimization interacts with the accuracy of the predicted target value by the process model. In order to define several parameter sets close to the target value, the movement of the particle swarm is supported by the best position in the target area (highest accuracy of the predicted target value by the process model). For prediction, feasible

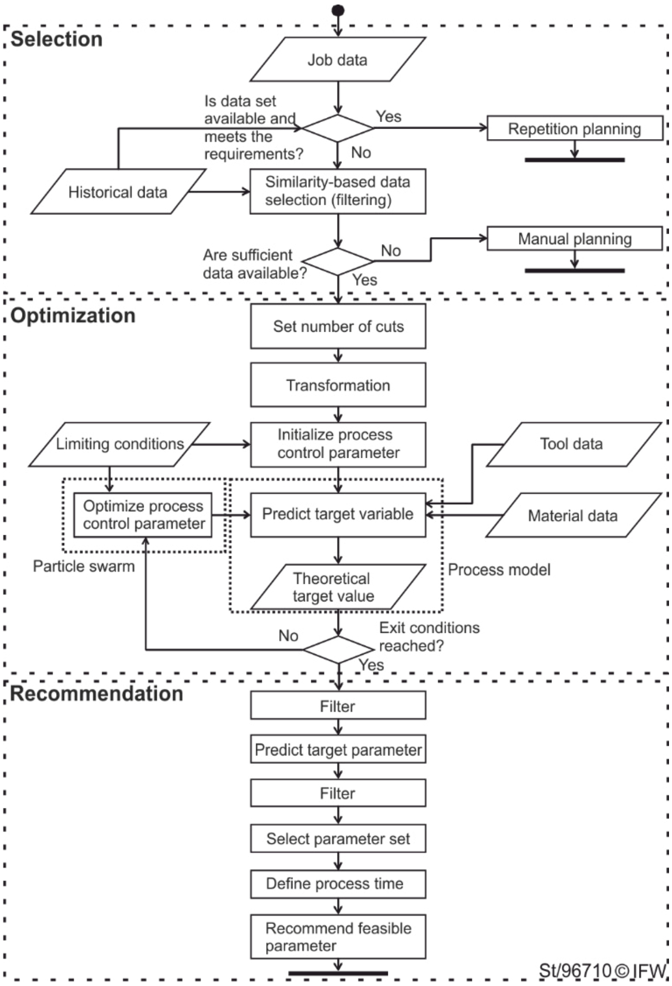


Fig. 3: Flow chart of knowledge-based process planning.

regression models have to be found to predict target values depending on the input, i.e. the focus of this paper. In addition, information from a material database and a tool database are used to consider further input variables. From the material database, characteristic values (e.g. material hardness) are extracted to inform the materials available in the historical information and the order data of the new production order. The tool database contains information on the tools used in previous production orders and on the tools available for the future production order (e.g. geometry, wear). After the prediction of the target values by the process model, it is checked whether the theoretically-determined target values have reached previously defined exit conditions. If this is not the case, the process control parameters are updated by the metaheuristic procedure. This update of the process control parameters takes place again within the defined limits, which were already used during the initialization of the start parameter. If the exit conditions are reached, the optimum process control parameters are available, provided that the tool used shows no wear. As a result, tool geometries and associated process control parameter can theoretically be used to achieve a specific target value.

### *3.3. Recommendation*

The optimization is followed by a recommendation of a feasible parameter set by filtering, because different parameter set combinations can create the same surface roughness. A recommendation of the tool is made by considering the tool-life in combination with the expected production time to avoid additional set up time. First, the list of feasible parameter sets is filtered according to whether the requirements formulated in the order data for the target variables can be met (e.g. maximal cutting speed). The final surface roughness is then determined based on the previously learned machine learning algorithm in the optimization section. If tools are directly assigned, their tool-life is taken into account. Afterwards, it is filtered again whether the requirements formulated in the order data for the target values can be met, since taking wear of the chosen tools into account can have a negative influence on the target values. Finally, a list of alternatives of different tools and associated process control parameters to meet the required target value can be achieved (e.g. surface roughness Rz = 0.7 µm).

Moreover, by using the Taylor relationship combined with the determined process parameter, the expected tool life reduction ($t_h/L_t$) is calculated. Compared with the tool replacement costs ($C_t$) of tool k, the cost for the use of the tool adds up. Furthermore, by taking the machine hour rate ($C_{Mhr}$) of machine j multiplied by the process main time ($t_h$) of parameter set (i) into account, the total cost for production ($C_{total}$) of a set of parameter can be calculated, as shown in Eq. 1. Thus, a feasible set of parameters with minimal costs is recommended.

$$C_{total}(i) = t_m(i) \cdot \left( C_{Mhr}(j) + \frac{1}{L_t(k)} \cdot C_t(k) \right) \qquad (1)$$

From the alternatives, the one that meets a certain criterion is selected (e.g. minimal total costs or minimal production time on equal costs). Finally, the tool database is updated in order to account for the changes in the tool life selected for the new production order and the process main time is calculated. In the last step, the specific, optimal process control parameter are output.

## 4. Experiments and results

In order to maintain and react to different or insufficient data sets, highly flexible regression models are required. The regression models should keep the influence of data set sizes on target value low. Therefore, they must be highly flexible with respect to the size of the input variables. The recorded historical data (e.g. workpiece geometry) differ depending on the sequence of ordered products. So far, this only works with large manual intervention in data mining. Hence, an experimental pre-study is conducted to identify the most feasible machine learning algorithm to predict the parameter set to achieve the target value. The experimental data set includes 124 data rows from longitudinal outside turning of unalloyed steel C22 (1.0402). The process is carried out on a Gildemeister CNC universal lathe CTX 420. In the experimental study, the input variables are modified discretely in a predefined experimental design. The cutting speed is set on 60, 120, and 180 m/min, the cutting depth on 0.1, 0.15 and 0.2 mm and the feed between on 0.05, 0.1 and 0.2 mm. Additionally, four different tools (indexable insert with variation tool angles α/γ of 35°/35°, 75°/45°, 75°/75° and 45°/75°) are used. The tool replacement costs are assumed

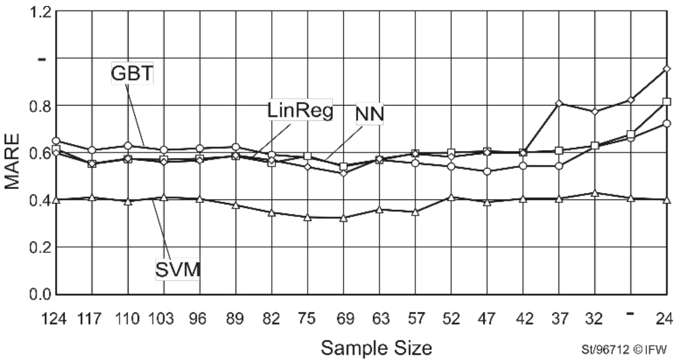


Fig. 4: Comparison of algorithm on C22 data set.

equivalent. Besides the cutting speed ($v_c$), the feed (f) and tool, the depth of cut ($a_p$), the obtained surface roughness (Rz), the tool-life and the number of cuts are recorded. Surface roughness is measured on an alicona InfinitFocus G5 optical measurement system. The algorithms are reviewed in the open source environment of RapidMiner Version 9.0.003 [20].

*4.1. Modelling of surface roughness*

In the literature, linear regression (LinReg), neural networks (NN), and support vector machine (SVM) are most common for predicting process parameters in turning. Despite promising results in other fields [17], gradient boosted trees (GBT) have not been applied for turning operations, yet. Thus, GBT have been included in this study as well. The GBT is specified by a number of 1000 trees, a maximum depth of 9 and a learning rate of 0.001. A 4-2-1 NN trained by 1000 cycles, a momentum of 0.91 and a learning rate of 0.008 is used. The SVM is characterized by max. 100,000 iterations, a trade-off variable (C) of 0.2 and convergence epsilon of 0.001. The evaluation is made concerning the mean-absolute-relative-error (MARE) of a leave-one-out cross-validation (LOOC). The optimization of the hyper-parameters was systematically carried out by monitoring the function. A statement about an optimum is only possible in the range of the varied hyper-parameter. In the optimization section, the need for a feasible and robust machine learning algorithm to predict the surface roughness (Rz) from cutting speed ($v_c$), feed (f) and depth of cut ($a_p$) is crucial. The results, shown in Fig. 4 and Tab. 1 differ in MARE; GBT at 0.65, the NN at 0.6153, SVM 0.4004 and LinReg at 0.5982. Consequently, this specific SVM is an appropriate algorithm to predict surface roughness. However, it is not possible to make an explicit and generally valid statement about the suitability of the algorithms, because of the small database and the relativized generalization. This has to be investigated in further research.

*4.2. Parameter selection*

Next, a set of process parameter for a surface roughness of Rz = 0.7 µm is carried out. In this case, the particle swarm optimization was characterized by 30 iterations, about 2000 particle (500 per tool), an inertia of movement (w) of 0.5, a cognitive weighting factor (c1) with 0.7 and social weighting factor (c2) of 0.7, which adds up to 60,000 results in varying parameter sets. The SVM provides 57 parameter sets with a target roughness of 0.7 µm. Depending on the equipped tools and tool-life filter (in this case, all 4 tools are set up and no tool wear is regarded) no further parameter sets can be filtered out. As known in literature, cutting speed ($v_c$) and the feed (f) have a significant influence on the tool wear and thus, on the tool-life. This is because, in some cases, it is worthwhile to take higher costs instead of longer production time in consequence of penalties due to delayed orders. This conflict between costs (represented by tool wear) and time (represented by cutting speed) has to be taken into account in the superordinate approach of economical re-scheduling. As an example, maximal feed strategy leads to a shorter production time. Hence, to aim a surface roughness Rz = 0.7 µm, a parameter set of cutting speed $v_c$ = 180 m/min, feed f = 0.1419 mm and the depth of cut $a_p$ = 0.1280 mm with tool 3 (75°/45°) is recommended at constant cost of tools and a non-observance of wear.

Tab. 1: Results of comparison on C22 data set.

| Machine learning algorithm | GBT | NN | SVM | LinReg |
|---|---|---|---|---|
| MARE | 0,6500 | 0,6153 | 0,4004 | 0,5982 |
| Std. deviation | 0,5516 | 0,5893 | 0,3535 | 0,5587 |
| Confidence interval 95% | 0,9029 | 0,8963 | 0,9378 | 0,9017 |

*4.3. Performance analysis with reduced training data*

In order to create a basic understanding of how much input is required for the algorithms to work, the influence of the size of the historical data set used on the predictive performance of the machine learning algorithm (to predict surface roughness) is investigated. To consider this issue, the data sets are reduced systematically, using clustering (k-Means with 100 optimization steps) and outlier cleaning. The aim is to divide the data points into a suitable number of clusters. To determine the optimal number of clusters, they are varied and evaluated by the silhouette coefficient [21]. Once the optimal number of clusters is determined, the data set is gradually reduced in size by filtering out a certain number of data points in each step. For each point within the cluster, the average distance to its 10 nearest neighbors is determined. The point with the largest average distance (euclidian distance) to its neighbors is filtered out. Each step in which the data set is reduced is followed by a prediction of the target values. In detail, the optimal number of clusters was determined (result: k = 7 is optimal number of clusters, silhouette coefficient of data sets is 0.445). Further, the set is reduced in size (delete 1 outlier from each cluster) and a LOOC is performed and repeated several times. The results of the considered algorithms are placed in Fig. 4 and Tab. 1. The performance is specified as a MARE. The performance of the algorithms is widely spread. The data set in Fig. 4 shows a consist graph among the size reduction. SVM performs the best, in comparison to the other algorithms. Considering the 95% confidence interval, the SVM shows the best performance even with the reduction of input.

In summary, a prediction of feasible parameters for longitudinal turning can be made using a particle swarm optimization combined with a support vector machine. The silhouette coefficient might be a necessary condition to evaluate the quality of clusters, yet it is not possible to take conclusions from the coefficient on feasible algorithms to predict process parameters in turning.

## 5. Conclusion

As shown in this paper, there is a need for a knowledge-based process planning in turning operations to derive reliable process times for re-scheduling. The knowledge-based process planning represents an approach that can fit the requirements from different levels of enterprise organizations and include process planning in a superordinate approach. In this paper, a set of parameters are predicted to meet a defined surface roughness by using a particle swarm optimization and a specific support vector machine. Hence, the studied algorithms can provide reliable process parameter. However, the results of the process modeling algorithms differ, depending on the database size. Therefore, no general statement on the suitability of the individual algorithms can be made. A better comparison requires a larger database of parameters, which is considered for future research. In addition, a solution is needed to provide algorithms, which are able to transfer knowledge from known materials to new materials. The research of the influence of insufficient data sets on flexible regression models needs to be focused. The function of data acquisition in industrial use is not considered in most approaches. In contrast, to use the approaches in industrial environment, data acquisition has to be taken more practically into account. Therefore, the approach has to be implemented in an executable application, the planning logic in re-scheduling has to be investigated and the superordinate approach evaluated.

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**Nomenclature**

| | |
|---|---|
| CAM | Computer aided manufacturing |
| ERP | Enterprise resource planning |
| GBT | Gradient boosted trees |
| LinReg | Linear regression |
| LOOC | Leave-one-out-cross-validation |
| MARE | Mean-absolute-relative-error |
| MES | Manufacturing execution system |
| NN | Neural network |
| SCADA | Supervisory control and data acquisition |
| SQL | Structured query language |
| SVM | Support vector machine |

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