Concept for Development Project Management by Aid of Predictive Analytics

Günther Schuh, Michael Riesener, Christian Dölle
RWTH Aachen University, Laboratory for Machine Tools and Production Engineering WZL, Aachen, Germany

Abstract--**Manufacturing companies in high wage countries strive towards shortened development and innovation cycles at decreased costs in order to strengthen their competitive advantage. These goals can be achieved by efficient development projects. However, approaches aiming at designing efficient development processes such as the value stream analysis only analyze development projects retrospectively as well as periodically and therefore do not continuously improve the efficiency of the respective projects themselves. Therefore, a concept is needed to anticipate deviations from the target process and thus inefficiencies within development projects by aid of predictive analytics. To derive a predictive analytics model, neural networks are applied to identify the impact of deviation indicators on the efficiency dimensions time, costs and quality of an activity. Upon reversion, it is possible to monitor the deviation indicators and use the respective indicator values as input for the neural networks. Based on the identified impact of the indicator on the efficiency dimensions, the neural network is able to predict the final values of an activity in terms of time, cost and quality. By comparing the predicted values with the defined target values, the deviation can be determined and preventive measures can be implemented to eliminate inefficiencies.**

I. INTRODUCTION

The manufacturing industry experiences growing pressure due to globalization and international competition. Companies are not only confronted with shortened product lifecycles, but also face rising quality demands for their products, which are linked to substantial customer requirements [18][23]. Shortened lifecycles need to be approached by high development speed and state-of-the-art development processes in order to increase the so called return on engineering, which is focused within the Cluster of Excellence “Integrative Production Technology for High-Wage Countries” [24]. In order to be successful in today’s competitive environment, it is a key to include ideas of Lean Thinking in the development process [13]. While continuously improving the efficiency of development projects by reducing waste and inefficient activities along the process chain, the customer’s benefit should consistently remain in focus. A study conducted by the laboratory for machine tools at RWTH Aachen University revealed that the majority of the participating companies (66%) were not able to identify wastage within their product development process [21]. However, especially in the early process stages development projects offer high improvement potential to maximize the benefit of the project for the customer as well as the company [25]. Value stream mapping is one method to address the mentioned issues through application of Lean Thinking concepts. Modelling the flow of information throughout the development process chain enables the exposure of optimizing potential [11]. Despite the positive effects, value stream mapping has significant weaknesses. The retrospective view on the outcome of a project and the periodically applied optimizations are the major downsides of this methodology. Additionally, value stream mapping is time consuming and can only be performed reasonably in large time intervals. Therefore, the overall effectiveness is limited and real-time project controlling cannot be realized due to the retrospective view onto the project. The Failure Mode and Effect Analysis (FMEA) [27] represents another approach to tackle the issue of development project optimization and reduce the risk of project failure. Instead of using the latest project data as input, this methodology relies on the experience and expertise of the project team. In conclusion, in this field of research, a new concept is required to extent the mentioned approaches by using existing project data from previous and present projects to predict deviations in running development projects.

This paper addresses the specified issues and presents a concept for the data based anticipation of deviations of activities by aid of neural networks and the derivation of a predictive analytics model. Comparable to approaches in the field of predictive crime analytics [15] – where reported crime offenses are used to create hotspot maps and perform proactive counter measures – artificial neural networks are implemented to process the gained data and anticipate deviations in development projects [18].

II. RELATED WORK

In the following, existing approaches for the steering and controlling of development projects will be introduced. Furthermore, approaches applying data mining in manufacturing companies as well as approaches aiming at controlling projects by aid of artificial neural networks will be described.

A. Steering of product development projects and innovation controlling

Within the scientific literature numerous concepts address the steering of development projects as well as approaches addressing innovation controlling. WERNER [28] focuses on a planning, management and controlling system which involves R&D activities to examine the current status of development projects and to identify potentials for improvement. In another approach by RIEDL [16], project controlling is considered as a key element of project management. In this context, the management of development processes is enabled by comparing the actual and nominal values of the previously defined KPIs. LEVARDY AND BROWNING [12] describe the development process as a complex, adaptive and self-regulating system. Therefore, they expand the A-priori consideration of product development processes by adding a project plan. Despite the determination of efficient activity sequences with the help of combination rules and simulation, no anticipation of deviations in order to improve the project management is supported. Finally, the concept of the Failure Mode and Effect-Analysis (FMEA) is used to avoid risks and mistakes in new processes and products [27].

The described approaches all focus on controlling and steering of development projects. Nevertheless, indicator based approaches are rather oriented on a retrospective controlling, whereas the FMEA is future-oriented, yet based on experience regarding potential risks for a project.

B. Data Mining and Predictive Analytics in manufacturing companies

Several approaches address the implementation of data mining and predictive analytics in manufacturing companies. However, most of these approaches focus on the field of production rather than on development projects. The few existing approaches within the field of product development aim at supporting product design and construction. Nevertheless, increasing the efficiency of development projects is not their main objective. Therefore, relevant approaches focusing on production followed by product development concepts are described.

The main target of most data mining approaches, which apply data mining within the area of production, is the definition of an optimal production strategy in dependency of the surrounding factors. STEINBACH [26] examines production processes and their interactions by applying data mining techniques in order to define an optimal production strategy. GRÖGER ET AL. [8] analyze factors with an impact on production processes in order to optimize and adjust these factors. SCHMITZ [19] develops a concept, which supports the derivation of product families based upon an analysis of feedback data from production and ERP-Systems.

Data mining approaches related to the area of product development mainly aim at defining design guidelines for new products. For example, ROMANOWKSI ET AL. [17] use product lifecycle data for the early development phase to prevent iterations. JIN ET AL. [9] attempt to accelerate the construction of new CAD-Models by identifying main design activities within existing CAD-Data. AGARD ET AL. [1] use data mining algorithms to identify product families, whereas new product specifications are derived by analyzing and assessing customer requirements.

In conclusion, existing data mining approaches do not address the issue of deviations in development projects and are furthermore incapable of anticipating these deviations. Instead, they mainly focus on optimizing the production or supporting the engineering and design process. The optimization of development projects in analogy to a value stream mapping is not covered by these approaches.

C. Project Management with the help of Artificial Neural Networks

Existing concepts applying artificial neural networks for project management, strive to predict the outcome and target achievement of a project. For example, ZHANG ET AL. suggest using artificial neural networks for industrial purposes due to the significant advantages of processing non-linear data and the ability to learn from completed development projects. The issue of choosing the appropriate and efficient artificial neural network in terms of size, structure and learning method is another key aspect in this concept [29]. In a more specific approach, KAUSHIK AT EL. estimate the amount of effort and development time in software projects by means of artificial neural networks. Their results demonstrate, that the mentioned method performs comparatively well, when input data is imprecise and uncertain. Therefore, the accuracy of software cost estimation has improved considerably when artificial neural networks are applied [10]. LIU ET AL. analyze and evaluate engineering projects by the aid of artificial neural networks. Time, cost, quality and safety are highlighted as the main drivers for successful projects, which combine for an overall evaluation score [14]. APANAVICIENE ET AL. apply artificial neural networks in the construction sector. The main focus of this work is the identification of key factors, which affect the outcome of construction projects, such as the competency of the project leader, the overall team experience or the influence of decisions during a project [2].

Though neural networks are already applied to predict a project's success and the adherence of the project targets, an analysis on an activity level of development projects is not focused.

III. METHODOLOGY

In the following, the concept for preventive project controlling of product development projects by aid of predictive analytics is described. First, an overall target image for the methodology is created as an introduction. Afterwards, the derivation of a predictive analytics model is described, before developing the actual predictive analytics model for the preventive controlling of development projects.

It is the aim, to develop a tool to visualize upcoming stages of a development project including anticipated deviations of activities. As shown in Fig. 1, the visualization associates the different activities to responsible departments and shows the interaction between these activities. By applying predictive analytics, the target adherence of each activity is rated and the impact of possible deviations of activities is analyzed. In combination, this allows the anticipation of a phase's target achievement in terms of time, cost and quality [7]. Whenever an activity's deviation is critical to the overall phase's goal, it is indicated by the tool and the project leader can implement preventive measures, thus preventing deviations from occurring.

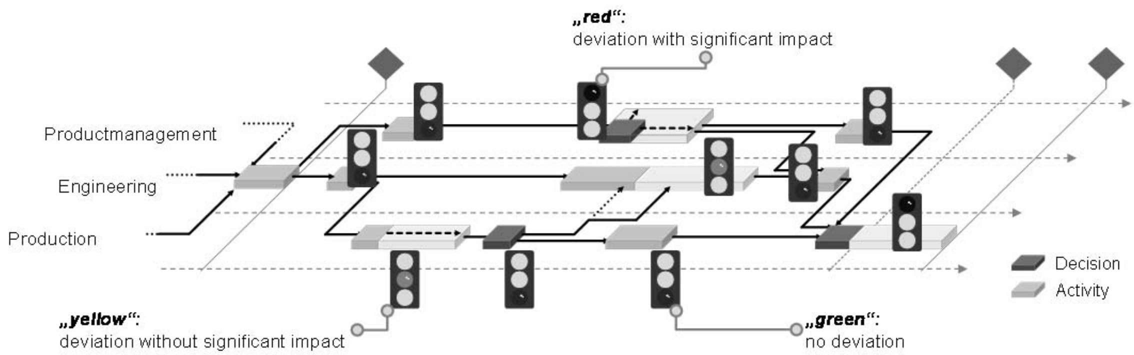

Fig. 1: Vision for the Methodology

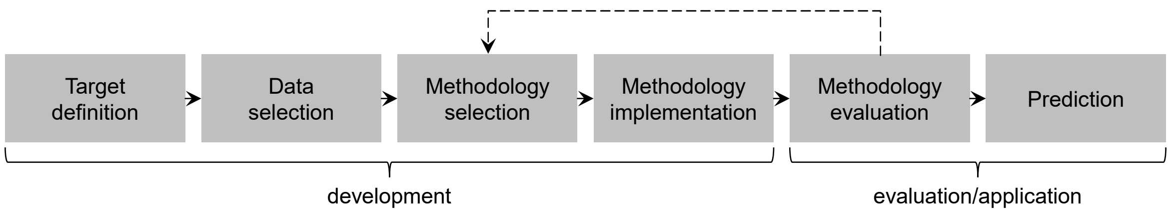

Fig. 2: Building a predictive analytics model [3]

In order to implement such a tool as described before, a predictive analytics model needs to be derived to anticipate the deviations of the activities within a development phase. The derivation of such a predictive model is the objective of this research paper. In general, a predictive analytics model is derived in six steps as it is illustrated in Fig. 2.

After defining the target of a predictive analytics model, the available input data needs to be determined to select an appropriate methodology for the respective problem. When the implementation and evaluation of the concept is completed, predictions may be made and in the present case deviations within the target dimensions can be anticipated. This paper focuses on the first four steps target definition, data selection, methodology selection and methodology implementation, when building a predictive analytics model. According to these steps, the methodology will be described in the following.

A. Target definition

The first step, when developing a predictive analytics model in general, is the target definition. Based on the target, it is then possible to define the data needed in order to make predictions and to select the methodology, which is applicable for the problem at hand. In order to develop a tool, which indicates possible activity deviations as well as their impact on a development phase's success, it is necessary to anticipate an activity's deviation from its target dimensions time, cost and quality (see Fig. 3).

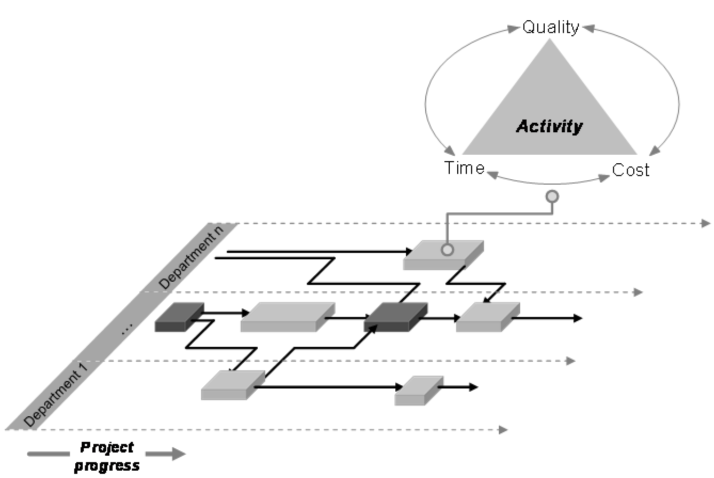

Fig. 3: Target definition

Therefore, it is the central objective of the predictive analytics model, which is developed, to anticipate deviations within the three target dimensions of an activity. In the following, it is described, which data is needed in order to make predictions regarding the deviation of an activity within the target dimensions and therefore to reach the defined target of the predictive analytics model.

B. Data selection

For the selection of the data needed to derive a predictive analytics model, it is reasonable to view a company, its processes and especially the development process from a system's point of view [11]. This allows the identification of relevant data for anticipating deviations of activities. On an overall-level the system *"company"* contains all relevant business processes [11]. Within this overall-system the "*development process"* as the sub-system and its system-elements represent the objective for the presented methodology. As a development project is the specific execution of the development process, it represents the reference process for all projects containing the different development activities as well as their interactions (see Fig. 4). Considering the interactions of all activities, which have to be completed within a development project, allows the analyzation of the effect of an activity's deviation on the target dimensions of a development phase. In order to anticipate deviations of an activity, such activities have to be analyzed on a system-element level [22] (see Fig. 4).

The system-element "*activity"* can be described by different characteristics (e.g. type of execution), its target dimensions (time, cost, quality), as well as the deviation from those targets caused by so called deviation actuators. The detailed description of these actuators as wells as their derivation will be described later on.

After the identification of the data available for the derivation of a predictive analytics model, this data now has to be described in a standardized manner in order to allow the application of data mining algorithms and to determine patterns of deviation occurrence. Following the system view, it is explained, how on the overall-system level activities are categorized to prepare them for predictive modelling. Afterwards, the parameterization of the deviations actuators is explained on the sub-system level. Comparable to the categorization of activities, the parameterization is necessary to allow the application of data mining algorithms and thus the connection of deviation actuators and the occurrence of activity deviations.

1. Description of activities

It is necessary to define attributes to describe all activities within a development project [18][23] in order to allow a comparison of the activities and to analyze the activities by aid of data mining algorithms (see Fig. 5).

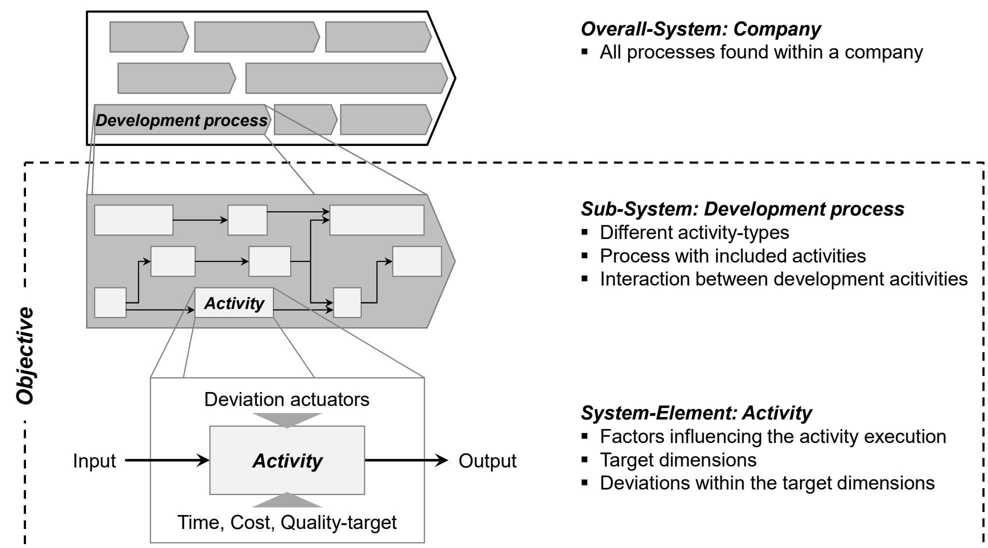

Fig. 4: Viewing the development process as a system [19]

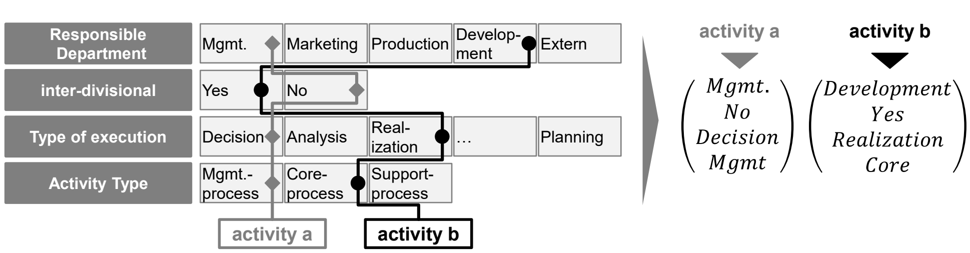

Fig. 5: Categorization of activities [23]

Primarily, activities can be divided by their value adding share in so-called "activity types". In case value is directly created by an activity, it can be described as a *core activity*. *Supporting activiti*es provide necessary resources for other activities and therefore have a lower value adding share. The superordinate *management activities* do not create value directly, but support and supervise the coordination and communication of other activity types [27]. The "type of execution" characterizes the activities and therefore helps to transform an activity's description, which is usually stated in prose, into a standardized format. In this paper *decision, analysis, realizations, planning, informing, steering, controlling* and *consultations* are derived from existing literature and are considered as the types of execution [20]. In addition to that, a connection between the activities and the executing departments has to be made. The attribute "responsible department" shows the allocation of the activities and executing/responsible departments. It also indicates whether or not an activity is executed by more than one department and therefore cooperation is required. Altogether, the mentioned attributes define an activity completely, as not only the general type is described, but also responsibilities and interactions between departments are exposed. As a result, a 4x1 – activity vector including all characteristics in the respective row can be formed for further steps [23]. The standardized format to describe development activities provides the possibility to calculate the similarity between activities and to identify clusters of similar activities by aid of cluster analyses. After the description and derivation of different activity types, the deviation actuators and their parameterization are described in the following.

2. Deviation actuators

Deviation actuators represent overarching factors within a product development project, which influence the execution of an activity and cause deviations. There are several studies, which strive to identify such factors (e.g., *communication, capacity, multi-project environment*) causing deviations within an activity's target dimensions [6]. To connect deviation actuators to the deviations of an activity and therefore to identify patterns between deviation actuators and deviation occurrence, the actuators have to be parameterized to be measurable and analyzable. The parameterization can be conducted by introducing deviation indicators, which can be identified by expert interviews and through project experience. Indicators, which are used for the parametrization of the deviation actuator "communication" are for example the number of e-mails send, the number of meetings or the meeting participation rate of the respective team members (see Fig. 6). In this context, the amount of e-mails related to a specific development activity describes the flow of information and the degree of cooperation within the project team. On the one hand, a comparably low number of e-mails could indicate poor communication, which may lead to deviations especially within interdisciplinary activities. On the other hand, a striking number of e-mails could be caused by problems, which demand intense coordination between team members. For an ongoing anticipation of deviations, it is necessary, that the identified indicators can be collected primarily automatically and continuously by aid of IT-systems (e.g. Outlook, PLM-software, etc.). In order to develop a predictive analytics model, such relations between deviation indicators and deviations have to be identified by aid of data mining algorithms. When these dependencies are determined, it is then possible to make predictions depending on the values of the deviation indicators. The selection of an applicable algorithm as well as the configuration of the algorithm for this task will be described in the following.

C. Methodology selection

In order to anticipate the deviation from an activity's targets, it has to be determined, how the combination of different deviation indicators affects the target dimensions time, cost and quality (see Fig. 6).

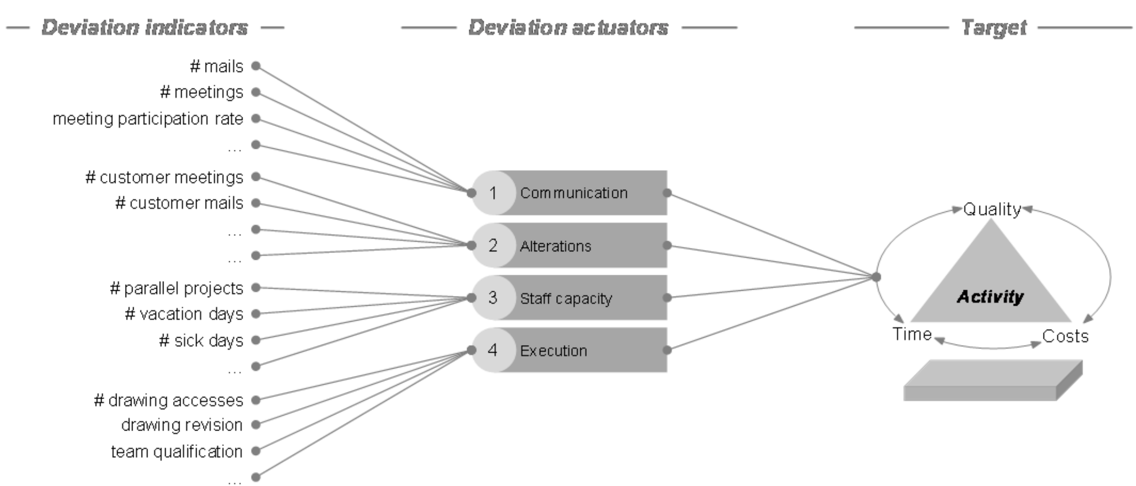

Fig. 6: For prediction, the deviation indicators have to be connected to the emergence of deviations

For the present methodology concept artificial neural networks are applied to derive the needed interrelations between the indicators as well as their impact on the deviation of an activity by aid of curve fitting. In this case, the neural network determines the impact of a combination of factors onto an output variable. By altering the combination of input factors the value of the output variable is affected as well. Transferred to the present case, it is possible to predict the percentage outcome of an activity within a target dimension, which can be described by a curve depending on the combination of deviation indicators. Through alteration of the deviation indicator vector, the final anticipated target value (e.g. in terms of activity duration) can then be determined by aid of the neural network.

The next step, methodology implementation, focusses on the development of a neural network for the present case, which allows the anticipation of an activity deviation in dependence of deviation indicators.

D. Methodology implementation

Before implementing a neural network for the present case, the fundamental structure of neural networks in general and the relevant key components of a neural network will be introduced. Afterwards, the development of a neural network for the anticipation of deviations on an activity level is described.

A neural network usually consists of three layers. The input layer contains the input factors (in the present case, the deviation indicators), which effect the value of the output layer (in the present case, the deviation of the respective activity). These two layers are connected by a so-called hidden layer (see Fig. 7).

The hidden layer contains neurons, which are connected to the different input variables as well as the output variable (see Fig. 7). There are several possibilities to determine a range for the number of neurons within the hidden layer, which then has to be finalized iteratively based on the output of the neural network [4]. Each neuron within the hidden layer as well as the output neuron inherit an activation function, which transforms an input value into an output value, enabling the mapping of input variables with the respective value of the output variable (see Fig. 7). For the present case, sigmoid functions will be used as activation functions for the hidden layer, as they allow "…smooth mapping between continuous variables" [5], and a linear activation function will be used for the output neuron [5]. In contrast to sigmoid functions, the linear functions do not have restricted output values [5], which therefore meet the requirements of this methodology as deviations within the target dimensions do not underlie any restrictions. Within the training process of the neural network, the weighting of the different interrelations is determined in order to consider the impact of different input variables onto the output variable. A trained neural network is then able to estimate the value of an output variable based on the values of the input layer [5].

Based on the experience in the field of development process optimization, a neural network (see Fig. 7) should be developed for each one of the three target dimensions, as deviations within the different target dimensions can occur under different circumstances. Next to the target dimension itself, the combination of deviation indicators leading to the emergence of a deviation also depends on the activity type. For example, deviations within realization activities in the development department occur due to a combination of deviation indicators that might not affect decision activities of the management at all or at least at a different intensity. As a conclusion, the three neural networks based on the target dimensions should be developed for the different activity types, which were identified by aid of the cluster analysis (leading to a total number of neural networks of "3 x #activity types"). To determine the proper amount of clusters a trade-off between anticipation precision and needed volume of training data has to be made. On the one hand, the anticipation is more accurate for a higher number of activity

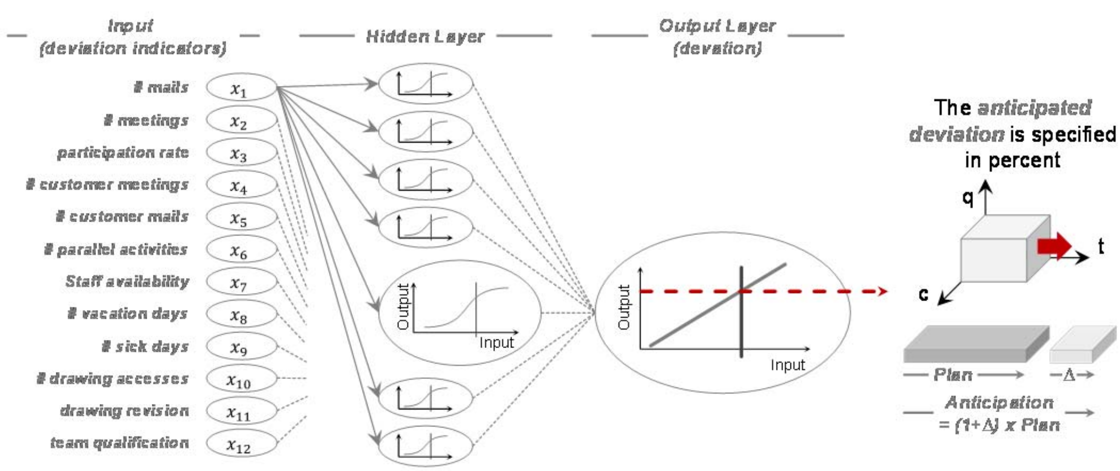

Fig. 7: Use of neural networks to connect indicators and derivations

clusters, as the clusters themselves are more homogenous. For activities within those clusters the circumstances (combination of deviation indicators), under which deviations occur, are more similar. On the other hand, a higher number of activity clusters demands more data to determine the interrelations within the network, since each activity type requires its own set of training data. The determination of the optimal number of activity types in relation to the available training data will be in the focus of future research.

The previous section described the development of neural networks in order to determine the interrelations between deviation indicators and deviations of activities within the target dimensions time, cost and quality by aid of neural networks. Such neural networks can then be used to anticipate deviations based on a combination of deviation indicators. Therefore, this section completes the actual development of the predictive analytics model, as the model can now be used to anticipate deviations on an activity level, which makes up the core of the overall target image for this methodology. The following section introduces an exemplary case study, which focuses on the development of a neural network for the target dimension time.

IV. EXEMPLARY CASE STUDY

As the presented methodology is a concept, which has to be validated in the future, a set of data (150 data points, consisting of 12 deviation indicator values (see Fig. 8) and a value for the target dimension duration/time) was constructed to derive a neural network, which allows the anticipation of the deviation within the target dimension time for one specific activity type. For the determination of the weightings within the neural network, the Bayesian Regularization was applied in MATLAB. The results of processing the exemplary set of data with an artificial neural network are shown in Fig. 8.

After training the neural network and thus determining the interrelations between the neurons within the network, a vector representing the current values of the different deviation indicators is entered into the neural network. Based on the indicator values, the neural network determines the duration of the activity in percent and the actual deviation can be derived. For the exemplary indicator vector the duration of the activity was indicated with “1,43” or “143%” of the planned duration. Originating from a planned lead-time (LT) of 20 days, the deviation of this activity is anticipated with 8 days. In a following step, it has to be analyzed, how this deviation effects further activities and thus the targets of the respective project phase.

V. CONCLUSION AND FUTURE RESEARCH

In times of shortened product lifecycles and rising quality requirements manufacturing companies aim at increasing the efficiency of their product development projects by eliminating waste and deviations. Approaches such as the value stream analysis or project controlling already strive to eliminate deviations within the project’s target dimensions. Nevertheless, these approaches are in the case of the value stream analysis retrospective or do not allow preventive controlling as deviations are only observed on a project-level. Though already applied to enhance project controlling, neural networks are not used to anticipate deviations on an activity level to support the project leader.

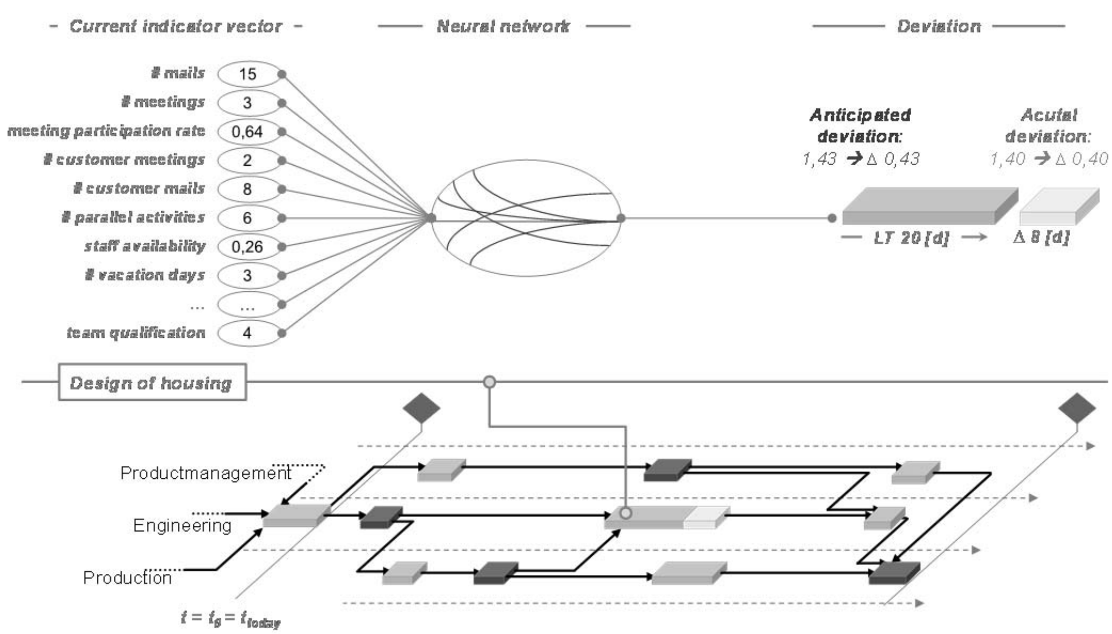

Fig. 8: By aid of the current indicator vector the deviation can be anticipated

The presented concept for "development project management by aid of predictive analytics" strives to analyze deviations of activities allowing the project leader to address deviations more target oriented and thus allowing a preventive implementation of optimization measures. By aid of preventive measures, the return on engineering can be improved, increasing the competitive advantage of companies.

The presented results are aimed at researchers as well as practitioners in the industry. With respect to the research community this submission is an important driver for the anticipation of deviations within product development project.

Further need for research lies within the further derivation of deviation indicators and the validation of the presented concept. In order to predict the impact of a deviation on a phase's overall targets, a risk analysis has to be developed, which considers the interactions between activities in terms of a sensitivity analysis. Furthermore, the development of a demonstrator would help to improve the practicability of the methodology for companies. Therefore, the concept will be validated in further companies in order to derive further requirements and to gain data for the validation of the methodology.

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