Elaborating Industry 4.0 compatible DSS for enhancing production system effectiveness

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Abstract. Developments on the base of the Industry 4.0 philosophy are the most important drivers of the recent production efficiency increasing activities. For meeting the requirements of the production facility operators, integration of digitalization-, virtualization-, simulation- and info-communication technologies are essential. Automatic detection and elimination of the errors in the actual production processes is one the most promising outcome of utilization of the data resulted by the online data acquisition and monitoring of the production system. Having these thoughts in mind, an innovative application of the discrete event driven process simulation on actual sensor data will be presented in this paper. Minimizing the idle times and maximizing the capacity utilization are the required consequences of this application.

Keywords. production process, discrete event driven process simulation, industry 4.0, production monitoring, data acquisition sensors

1. Introduction
Impacts of the recent developments in info communication technologies became part of our everyday life. Widespread use of mobile phones rapidly contributed to the development and use of online marketplaces and e-commerce solutions. As a result, production and service companies shortly faced the challenge of processing and fulfilling on-line orders and requests on a level that they were not ready to handle. Despite such customer orders are usually random considering time and amount of purchase, fast, prompt and high quality fulfillment has to be ensured. Complying such requirements with traditional production systems optimized for mass production is hard and costly, as medium or small quantities has to be produced with widening and continuously changing product scale. Frequent change in production results in losses both in production and logistics.

Thus, processing online orders call for a flexible production system where even special customer requests can be fulfilled without losses. To supply such production systems with parts and materials improved logistics are needed: JIT/JIS supplies shall be managed even in production-stock relations. Such goals can be achieved by strong co-operation between production and logistics: prompt and adequate data interchange using up-to-date communication channels. The need for increased flexibility and custom manufacturing induced the development of production systems where universal and autonomous equipment communicate and co-operate to reach a common goal: to produce a product item. As equipment status can be monitored by sensors in such a system, production effectiveness can be improved through decision making based on collected sensor data. Industry 4.0 focuses on this approach.
2. Digitalisation
As huge number of parameters is typical for complex production-logistic systems, high level computerised representation can be a suitable tool for their monitoring, analysis and characterisation. Tools with dynamic process modelling capability can be used to determine optimal parameter values. Primary goal of this modelling is to enable experiments in the system without interfering with the processes in the real system [1]. Data acquired from the real production systems have to be processed displayed and transferred by means of modern IT technologies for the process simulation [2][3]. Two main categories of production system models are as follows:

- Models based on static data preloaded from a database: In case of these passive models time dependency of indicators in the system can be described using the simulation; and results can be used to predict the performance of the real system using predefined KPIs. Thus, such models are suitable not only for optimisation and KPI improvement, but also for intervening Figure 1 a).

- Models based partly on sensors collecting data from the real production system Figure 1 b): In case of such active models a Cyber Physical System (CPS) [4][5] is generated according to the Industry 4.0 philosophy that integrated the five architectural levels of CPS. Data access that is needed for the simulation is carried out either via direct communication and data interchange or through common databases (Smart Connection-, Data Conversion Level). Measured sensor data is continuously evaluated, thus comparing system KPIs with pre-calculated values are executed even real time. Mitigation and intervention measures can be evaluated immediately if significant difference is emerged between real and target KPI values (Cyber and Cognition Level). Changing parameters in the real system can either be carried out by direct access through the available communication channels or by indirect human interactions (Configuration Level). Such models and simulation techniques are suitable for real time, parallel evaluation of real system data and detection of problems in the real system through the changes in parameter values and for decision support for mitigation and intervention.

3. Concept of a decision support tool based on active simulation models
A digital twin can be developed according to the digital factory concept based on the data collected in the real system real-time [6]. The digital twin can be used not only for monitoring parameters of the real system, but also for defining and managing intervention measures to improve system performance in case of insufficient KPI values (Figure 2).
Data that originated from the real production systems through the acquisition mechanisms of the different types of sensors is essential for the appropriate functions of the digital factories. The data transfer between the sensors and the digital factory can be realized by IoT solutions directly or indirectly through database tables either. The digital factory receives, processes and evaluates the sensor data continuously. Establishment of a digital factory could be carried out in the Siemens Plant Simulation software that is developed for modeling and for discrete event driven simulation of production and logistic processes [7]. It supplies with the object classes and with the communication interfaces that are necessary for the process modeling:

- socket communication for sending and receiving data through the specified IP address and port;
- ODBC related objects for accessing databases that are located on shop floor computers or on computer networks or in remote clouds;
- interfaces for accessing SQLite- or Oracle databases.

Requirements against the Decision Support System to be developed can be summarized as follow:

- digitalization of a real production system has to be supported;
- support for communication and for data transport among the system elements (e.g. sensors and databases) is necessary;
- ability of near-real-time monitoring of the production system parameters and ability for detection of the deviances arisen between the actual values of the system parameters and their targeted values;
- support for performing the necessary interventions automatically (e.g. setting the system parameters to the targeted values).

4. Demonstrative setup of the Decision Support System
A DSS prototype was elaborated to demonstrate the features and advantages of the digital factory application (Figure 3).
Figure 3 shows the flow-shop model [8] based illustration of a real production system which assembles different kinds of products \( P_i \). The sequence of the assembly operations is predetermined which means that the same types of products are follow the same path among the production steps. A production machine \( M_1, ..., M_n \) performs one assembly operation at once and there is no operation interruption permitted. The assembly operations cannot overtake each other. Every operation has its own time consumption which is necessary for assembling all the parts into the products at that specified production machine. There are 3pcs. of enumerated part storages \( S_1, ..., S_n \) allocated to each of the machines. Storage \( S_1, ..., S_n \) is dedicated to a specific part therefore a part can be placed only into its dedicated storage at the machines. The part consumption of an assembly operation depends on the type of the product to be assembled. The semi-finished product transports between the operating machines are characterized by the transport times. There are two types of data collection sensors applied in the system. Weight measuring sensors were applied for monitoring the part consumption at the production steps. These sensors supply with all the necessary information to calculate the intensities of the part consumptions. These intensities can be calculated by part types, and by part storages etc. RFID sensors \( R_1, ..., R_n \) were applied for identifying the type of the actually assembled product and for identifying the parts that are assembled into them. There is a possibility to identify the parts or products individually which enables the integration of advanced production track&trace functions into the DSS. The central component of the system is a database - Figure 3 b). It comprises on one hand the sensor supplied dynamic data and on the other hand the static data which is related with the construction and the set-up of the digital model of the production system:

- bill of materials (BOM) by product types;
- characterization of assembly steps by product types (including machines, time consumption, sequence, etc.);
- semi-finished product transport times between the production machines;
- lists of production machines, of part storages, of part types and of sensors.

However, all the data which describe the preliminary conditions of the simulation examinations on the digital model of the production plant are stored at the same database also. For example the production plan which determines the quantities, the types and the sequence of the products to be assembled can be stored there. There are data management mechanisms integrated with the central database also. Continuous comparison of the sensor bound data and the results of the simulation examinations are the main function of these mechanisms. Detection of the deviances and errors that may arise during the production process is the reason behind this comparison. Another element of the DSS system is the digital model of the production plant - Figure 3 c). This model is built within the Siemens Plant Simulation software. Giving possibility for simulation examination of the production processes is the main function of this system component. The production plan and all the production related preliminary conditions including the production supply processes are taken into account during
this simulation examination. The result of a simulation examination is called reference status time series (RS) for the examined future production period. Predicted values of the necessary process indicators and their changes during the examined future time period are included in the reference status. The following Key Performance Indicators of the production system are determined [9]:

- regarding the production processes:
  - utilization of the production machines;
  - productivity;
  - production lead times;
  - overall equipment effectiveness (OEE) [10].

- regarding the production supply processes:
  - capacity utilization of the part storages;
  - indicators of the part supply processes;
  - effectiveness of the warehousing and commissioning processes.

The reference status time series describes the progress of the production from the viewpoint of the actually assembled products and the quantity of the products that are already completed besides the already mentioned data. The DSS continuously compares these results to the sensor bound actual data. Stochastic effects that might be arisen at the real production can cause deviances \( K \) between the actual data and the reference status time series. The actual production process can be qualified to be in normal status (NS) depending the measures of this deviance. There are several indicators that have to be taken into account during the qualification of the actual status of the real production system. The indicator \( I \) of the part consumption \( \kappa_{s_i} \) and the indicator of the production intensity \( \kappa_{r_j} \) are among these indicators. The deviance regarding these indicators can be calculated with the following formulas:

\[
\kappa_{s_i} = |I^R_{S_i} - I_{S_i}^*| \leq d_{s_i} \tag{1}
\]

\[
\kappa_{r_j} = |I^R_{R_j} - I_{R_j}^*| \leq d_{r_j} \tag{2}
\]

The members of these formulas are the following:
\( \kappa_{s_i} \): deviance between the value \( I_{S_i}^* \) that supplied by the i. weight sensor and its reference value \( I^R_{S_i} \) at t. time [%];
\( \kappa_{r_j} \): deviance between the start time \( I_{R_j}^* \) of an assembly operation that registered by j. RFID sensor and the reference value \( I^R_{R_j} \) of this event [%];
\( d_{s_i}, d_{r_j} \): the predetermined maximum of the deviations between the sensor bound data and their reference values [%].

Average deviance [%] of aggregated indicators regarding the data that supplied by the weight and the RFID sensors:

\[
K = \frac{\sum_{i=1}^{n} \kappa_{s_i}}{n} + \frac{\sum_{j=1}^{k} \kappa_{r_j}}{k} \tag{3}
\]
where:

\( K \) : means the average deviance [%] between the real production system and the reference value which is calculated on the base of the simulation examinations.

Behaviors of the production capacities may influenced by stochastic errors. These stochastic features have effects on the production procedures continuously. Some of them strengthen each other’s effect and some of them weaken it. Overall influence of these effects on the production system can be qualified to be negative because it often manifested in efficiency reduction (e.g. daily production plan cannot be fulfilled). The reference status is calculated with having ideal production circumstances in mind. Therefore the reference values of the indicators can be the base of the comparison for detecting the deviances. The reference status (RS) means the forecasted time series of the production indicators, sensor bound data represents the actual values of these indicators. Probably there will be always a deviation among these values. This overall deviation is characterized by the value of the \( K \) which is calculated continuously during the real production process. The production process state can be qualified to be normal while the \( K \) value does not exceed a predetermined maximal value \( \varepsilon \):

\[
NS = RS \pm K \quad (K \leq \varepsilon)
\] (4)

A failure status (FS) developed if the value exceeds its limitation. This failure can be caused by an external impact which has significant influence on the production system. (e.g. raw material shortage):

\[
FS = RS \pm K \quad (K > \varepsilon)
\] (5)

There is a necessity for intervention into the real production procedure in case of such failure status. The aim of this intervention is to mitigate the effects of the errors and to ensure sustainable normal production circumstances. A new reference status has to be calculated after the interventions as production circumstances are characterized by the preliminary production conditions. The following Table 1 contains sample values of the sensor bound data and of their reference values for explaining the relation between the deviations and their possible appearance in the production system.

**Table 1. Sensor bound data and their reference values**

| \( R_i : M_i \) | Reference status (\( RS \)) (between 3h – 4h) | Real production system (*) (between 3h – 4h) | Deviances |
|-----------------|---------------------------------------------|---------------------------------------------|------------|
| \( R_1 : M_1 \) | P3, P2, \( P_1, P_3, P_4, P_5 \), P1, P2, P2, P4, P3 | \( P_3, P_2, P_1, P_3, P_4, P_5, P_1, P_2, P_2, P_4, P_3 \) | \( t^{RS}_{(3h)} : P_1 \) |
| \( M_1 \) production quantity | 20-25pcs | 18-23 pcs | \( t^*_{(3h)} : P_3 \) |
| \( S_1 : T_1 \) | 180 pcs | 192 pcs | \( t^{RS}_{(3h)} : 20 \) |
| \( S_2 : T_2 \) | 80 pcs | 95 pcs | \( t^*_{(3h)} : 18 \) |

(3) : \( RS \) (3) : \( t^{RS}_{(3h)} \) (3) : \( t^*_{(3h)} \) (3) : \( RS \) (3) : \( t^{RS}_{(3h)} \) (3) : \( t^*_{(3h)} \)
The data that collected by the \( R \) sensor confirm the production delay compared to the Reference Status. \( M \) production machine accomplish 2pcs fewer assembly than it was forecasted to the specified time interval. This delay is the reason for the greater amount of parts left in the part storage at this machine. Increasing delay will have impacts on the part supply processes as well. There will be more parts in the part storages than it was expected at the time of the part delivery. Parts that exceed the storage capacity of the storage place have to be returned to the warehouse. This part return process means unnecessary work and it decreases the efficiency of the part supply system. Early detection of the errors and determining their types is necessary to avoid situations with failures. A possible intervention to solve the situation that is described in the Table 1 is to increase the assembly speed at the \( M \) machine or to apply a redundant unit in parallel with \( M \). Synchronizing the production and the production supply systems is marked to be the further aim of the DSS. By determining the decreasing intensity of the parts in the storages next to the machines the time of the shortage can be calculated precisely. Therefore the warehouse subsystem can schedule accurately the preparation procedures of the parts and punctual preparation increases the efficiency of the part supply procedure. The DSS system continuously evaluates the operation of the production system as it was described above. It can propose intervention in case of significant deviances. Its activity facilitates the application of JIS methods in the part supply process [11][12]. Furthermore, only the necessary quantities of the parts have to be located next to the machines by means of the DSS therefore logistic related areas could be transformed into productive places in the plants.

5. Decision support system
The system concept of an industry 4.0 compatible DSS was described in the previous chapters. Its main function is the continuous comparison of the forecasted and the real values of the process indicators to preemptively detect the production errors:

- determines the location and the type of the errors;
- supports the decision regarding the most effective way of the intervention if it is necessary;

Hierarchical levels of the system are represented in Figure 4. based on the concept introduced in Figure 2.

![Figure 4. System concept of an industry 4.0 compatible DSS](image)

The real system itself is situated on the lowest level of the hierarchy, with the sensors – the data collection units – connected to them. The next level covers data collection, processing and storage, which processes and stores data on collected by sensors and calculated for reference status characterisation into an appropriate database. While third level contains the digital model of the
system, the top level represents the decision support system that makes decisions on intervention based on the previous levels results. Generalised operation process of a DSS is represented in Figure 5 [13].

![Figure 5. DSS [13]](image)

While problem identification is the first step towards a DSS, categorising such problems for identifying mitigation measures are next. As several ways may be available to mitigate impacts or eliminate errors, these possible ways have to be generated in the model and their side-effects have to be investigated. Intervening may be carried out either manually by operators or automatically directly by the DSS according to the rules defined for the error type. Despite operation of the DSS being simple, types of errors can be numerous due to the complexity of the real system. As a result, number of mitigation measures or error elimination procedures may be high. Next step of the development will be the development of a powerful decision support algorithm based on the aforementioned.

6. Conclusions
A possible use of digital factory approach, a central element in Industry 4.0 philosophy has been introduced in this paper: stochastic impacts causing errors in a real system can be calculated using digital factory models. Earliest possible identification of errors occur is crucial to determine the best way to intervene the system operation. Defining and categorisation of errors may lead to an effective decision support system suitable for error avoidance.

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