Design and Implementation of a Decision Support System for Production Scheduling in the Context of Cyber-Physical Systems

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Abstract. The use of cyber-physical systems in production promises great potential for production scheduling since a larger information base is available for the scheduling of production orders. However, the mere acquisition of real-time data does not inherently lead to improvements. On the contrary, a targeted preparation of the data is required in order to prevent an information overload. Decision support systems that support decision makers in production scheduling can perform this task. However, the design of such systems in combination with cyber-physical systems has hardly been investigated so far. In this paper, we therefore design and implement a corresponding decision support system in a design science approach. For this, we identify meta-requirements based on a literature analysis and an interview study. Finally, we evaluate the created meta-artifact in a laboratory setting in order to obtain generalizable knowledge about building such a decision support system.

Keywords: decision support system, production scheduling, cyber-physical systems, industry 4.0, design science research

1 Introduction

The increasing diffusion of cyber-physical systems (CPS) in companies creates a multitude of new possibilities to improve company performance based on real-time data. In particular, production scheduling, which is responsible for planning, executing and monitoring released production orders, can benefit from the new data availability. For example, CPS data can be used to monitor the status of orders and machines or to identify deviations from the plan (e.g., due to a machine breakdown). In the event of deviations, real-time data can also help to improve decisions about whether and how to react to those deviations by improving the assessment of the situation [1]. However, the mere availability of real-time data from production does not inherently improve production planning and execution in practice. Rather, the data need processing and aggregation according to demands in order to serve as a basis for assessments and decisions. Decision support systems (DSS) can provide such a decision basis and thus support decision makers in production scheduling [2].

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Although the use of DSS in production scheduling is not a new concept, research has not yet sufficiently addressed the possibilities offered by integrating real-time data from CPS nor is it widely considered in practice. Especially with regard to the design of solutions for decision support in the context of CPS, there is still a lack of knowledge. On the one hand, there are only a few research approaches and on the other hand, they usually lack generalizability. Therefore, the aim of this paper is to provide a design science research contribution and thus to create a foundation for general design principles [3]. In order to achieve this aim, we address two research questions:

RQ1: How should a software artifact that supports decision making in production scheduling in the context of cyber-physical systems be designed?

RQ2: How do users evaluate the application in a scenario-based laboratory setting?

In order to answer these questions, the remainder of this research paper proceeds as follows: In the next section, we describe the basics and outline related research. Thereafter, we present the applied research design based on the problem-centered design science research approach by Peffers et al. [4]. Afterward, we present the findings of applying this framework to our problem domain by stating (meta-) requirements, a software artifact and the results of its evaluation. In section 5, we discuss our findings, outline research contributions, and present limitations as well as future research directions.

2 Basics and Related Research

In general, production scheduling as well as DSS are widely researched already and therefore have commonly accepted definitions. **Production scheduling** is part of the production planning and control (PPC) and describes the time-related allocation of tasks to production resources in order to create a processing sequence for released orders, taking into account the underlying objectives (e.g., adherence to delivery dates or minimization of lead times) [5]. Since sequencing is a mathematically complex optimization problem, heuristics based on priority rules (e.g., due date rule or first-in-first-out) are used in practice to achieve the desired goals [5]. Furthermore, the fulfillment of the plan is monitored within the production scheduling and, in the event of deviations, countermeasures such as rescheduling or repairing are taken [5, 6].

DSS, in general, are defined as "computer technology solutions that can be used to support complex decision making and problem solving" [7]. They focus "on supporting and improving managerial decision making" [8]. Therefore, they are primarily used to solve semi-structured or unstructured problems [9]. To support decision makers, DSS are interactive systems that utilize models, methods and problem-oriented data to provide and edit required information [9]. DSS help to monitor business activities and processes (e.g., by using alerts when metrics fall below predefined thresholds), to analyze root causes of problems (e.g., by multidimensionally exploring relevant information), and to manage processes as well as people in order to improve and optimize decisions [10]. In the context of production scheduling, DSS shall provide the decision makers with alerts and

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information on the effects of deviations or (re-)planning options and support them in the associated decisions.

CPS, in contrast, have only been a subject of research for about ten years since first mentioned by Lee [11]. In the course of concepts like Industry 4.0 or Internet of Things (IoT), the discussion about CPS gained further attention since CPS provide the technological foundation of those concepts [12]. From a technical point of view, CPS are embedded systems that integrate physical objects, computation, communication, and networking processes [13]. "CPS can be illustrated as a physical device, object, equipment that is translated into cyberspace as a virtual model" [13]. They feature physical components like sensors and actuators to interact with their surroundings as well as networking and processing capabilities to process and communicate information. They are therefore able to monitor and control physical processes, usually with feedback loops where physical processes affect computations and vice versa [11].

Research regarding the use of DSS in production scheduling in the context of CPS has been neglected so far. Even though prior research in the area of production scheduling in the context of CPS as well as the use of CPS-based real-time data in DSS exists and already addresses some factors regarding the interplay of all three topics, a targeted examination is missing. In most cases, the existing contributions focus on the changes of process scheduling caused by CPS. The authors primarily deal with the effects for PPC systems and describe theoretical potentials as well as technical hurdles [14]. Mieth et al. [15], for example, describe how real-time data can improve the simulation of production. Karner et al. [16] use real-time machine condition data to improve production planning. Jiang et al. [17] and Dafflon et al. [18] at least include decision making of systems in their publications. The former developed a decision model for a multi-agent system that can dynamically adapt the planning. Dafflon et al. [18] describe a system that provides the decision making basis for a self-adaptive production system. Moreover, many of the prior contributions only refer to specific industry sectors [19] or cases [2], so that it is not possible to make general statements.

Only a few authors at all include DSS in their consideration. Those who do so, primarily deal with general challenges for decision support in production planning [20], the necessity of DSS in production planning [1] or how a DSS can make use of real-time data in PPC [21]. Two publication previously developed a CPS-based DSS for PPC. Schuh and Fuß [22] developed the ProSense application. However, their application aims at being self-optimizing and focuses on production monitoring. The DSS developed by Schreiber et al. [23] is further limited mainly to maintenance planning. Furthermore, both authors did not present their requirements and design principles in a structured or generalizable manner. Consequently, rigorous research that identifies how to design and implement DSS in production scheduling in the context of CPS is missing. Hence, there is a need to address and answer our research questions.

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3 Research Design

In order to address the research questions stated in Section 1, we chose the problem-centered design science research approach [4] as depicted in Figure 1.

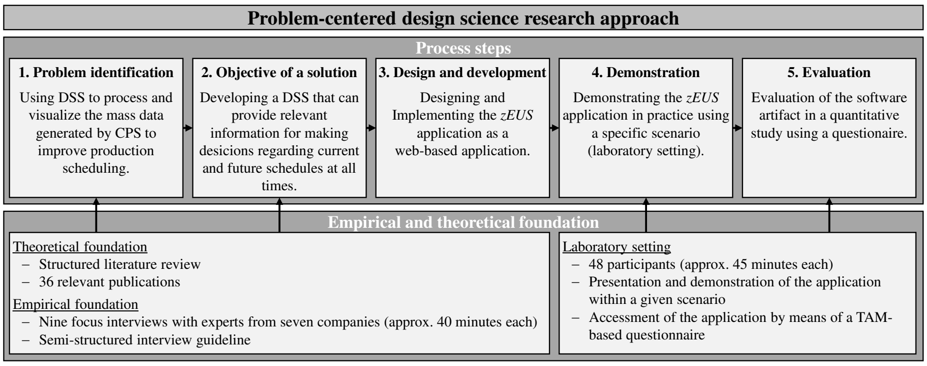

Figure 1. Research design adapted from Peffers et al. [4]

According to this approach, our first step is problem identification. In order to obtain both a theoretical (rigor) and an empirical foundation (relevance) of the problem, we conducted a structured literature review as well as a qualitative and explorative interview study. The literature review is based on the structured approach [24, 25] and covers 36 relevant articles, which build the basis for our research. In order to enrich the corresponding result with empirical contents and to ensure the identified issue is a real-world problem, we further conducted nine focus interviews with experts from the industrial sector and analyzed our results according to the structured content analysis approach [26, 27]. Based on the identified problem, we derived the objective of our solution and manifested it in the form of functional requirements in the second step of our research approach. In the third step of the design science research process, we used our requirements to deduce meta-requirements. Those build the basis for the implementation of a prototypical meta-artifact, called *zEUS*.

We then demonstrated the resulting prototype to 48 potential users in a laboratory setting in step 4. Therefore, we created a scenario of a production environment. That way, we could make sure, that we meet required frame conditions (e.g., availability of sensor equipment, devices, and networks) and provide a realistic configuration. In this scenario, the participants applied the prototype to master some production scheduling related tasks [28, 29]. Afterward, to cover step 5, we asked the participants to fill in a questionnaire, which is based on the technology acceptance model (TAM) [30]. The possible answers were standardized by means of a five-level unipolar Likert scale (1 = fully disagree to 5 = fully agree) [28]. The aim of this quantitative study was to evaluate the suitability as well as the usefulness and the usability of the developed prototype. Therefore, the participants consisted of practitioners as domain experts (n=8), research associates with an economic background as experts in designing and

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developing prototypical artifacts (n=15), and students with theoretical knowledge of PPC in particular as well as of economics in general (n=25).

4 zEUS Application

In the following subsections, we present the design and implementation of the *zEUS* software artifact to support the decision making in production scheduling in the context of CPS. The explanations within the subsections are divided into the ***representation of the current situation*****,** the ***detection of deviations*** and the ***reaction to deviations***, as these are the tasks of production scheduling and the areas of application of DSS and thereby form a common basis [5, 10].

4.1 Problem Identification

With regard to the ***representation of the current situation***, the starting point is the multitude of information and information sources. For example, presenting the current situation requires real-time data from the shop floor [1, 31] and information from systems relevant to production (e.g., ERP) [32, 33]. This mass of information must be collected, processed and presented in real-time in a form that is comprehensible for the decision maker [19, 20, 32]. One of the experts whom we interviewed summarized the situation of the representation of the current situation as follows*: "Today's systems remained on MS DOS level, they spit out a few numbers and then you have to know exactly what those numbers mean. This has to be much more intuitive"* (expert H)

With respect to the ***detection of deviations,*** the initial problems are similar, since the same information are required and must be merged [1, 34]. Furthermore, real-time evaluation and processing of the information are necessary in order to identify the deviations promptly [32, 34]. Additionally, it is difficult to precisely localize the problem situations and visualize them appropriately [1]. In this respect, expert D indicated: *"It would also be interesting to know, which orders we have to prioritize, what we can further release to production, how busy which plants are or which capacity is omitted by an error. Therefore, including all this is desirable in any case, but we are not that far yet."* (expert D)

When ***reacting to deviations***, a lack of information complicates assessing the occurred events, identifying possible reactions in response, and assessing their respective impacts [1, 32]. The lack of information often leads to decisions based on experience or gut feeling [1]. In addition, a complete rescheduling is a common reaction. Since this is time-consuming, it may cause the plan to become obsolete even before it is implemented [35]. An expert described the current situation in his company as follows: *"That are things we manually collect today. What does it cost? Where is our customer located? Then we go through all that together and in half an hour we have it all cleared up and decided how we do it. If there is such a system that, at the push of a button, provides the results like special trip is the cheapest, night shift is the most expensive. Then that's definitely a decision support."* (expert H)

In conclusion, the current problem is a lack of possibilities to collect, process, evaluate, and present the multitude of data sources and data in real-time in order to create a single source of information as a basis for decision making and thus improve production scheduling.

4.2 Objective of a Solution

In order to address all the problems mentioned above, we aimed at developing an artifact covering all three areas of application. In addition, the software artifact must visualize data, generate notifications as well as information, and interact with the user (e.g., to configure a simulation). For this purpose, it must collect, process, and present current data from the production as well as from the application systems involved in a quickly accessible form. This leads to the following objective of the solution:

The aim of the DSS is to provide decision makers with an informative and clear decision basis for decisions regarding current and future production scheduling at all times. The support must cover the presentation of the current situation, the detection of deviations, and the reaction to these deviations.

Based on this objective, we identified functional requirements for each area of application of the prototype. First, the ***representation of the current situation*** requires functionalities to collect (FR_{rcs}1-4), aggregate (FR_{rcs}6-9) and present (FR_{rcs}10-13) data. This data can originate both from the connected application systems as well as from CPS. Since the existing application and sensor landscape in companies may vary, a differentiation of the data type instead of a differentiation of the involved systems is recommendable for setting up the requirements. From a data perspective, production process data (e.g., workstations or machines), supplier data (e.g., suppliers or materials), production data (e.g., current events) and order data (e.g., customers or delivery dates) must be taken into account [22]. In addition, it is necessary to enable manual data input (FR_{rcs}5) in order to enter data if automated data acquisition or transfer is not possible (e.g., manual entry of an employee's absence) [36, 37].

In order to provide an overview of the whole production schedule, it is necessary to enable a complete representation of all data. For this purpose, the data types mentioned above must be correlated (FR_{rcs}14). Based on this correlation, the entire current schedule can be displayed with all associated information (FR_{rcs}15) [1]. Expert H from our interview study summarized those requirements by saying: *"[The System should] collect data automatically, automatically analyze, level, and distribute it."* (expert H) Table 1 shows an overview of the identified requirements.

Table 1. Functional requirements for the representation of the current situation

Requirement	*Description*
FR_{rcs}1-4	Collect production process data (1), supplier data (2), production data (3), order data (4)
FR_{rcs}5	Enable manual data input
FR_{rcs}6-9	Aggregate production process data (6), supplier data (7), production data (8), order data (9)

$FR_{rcs}10$-13	Present production process data (10), supplier data (11), production data (12), order data (13)
$FR_{rcs}14$	Correlate data
$FR_{rcs}15$	Present current production schedule

To realize the ***detection of deviations*** and their impacts, the DSS must analyze the acquired production data ($FR_{dod}1$-4). This again includes the four data types [38]. The identified events must then be categorized ($FR_{dod}5$) in order to present the cause of the events and to be able to react to the events [22, 39]. Exemplary event categories may include machine breakdowns or deviating set-up and production times. Furthermore, the system needs to display the categorized events to the user ($FR_{dod}6$) [38].

For each of the detected events, the impacts must further be determined ($FR_{dod}7$) and indicated to the user ($FR_{dod}8$; e.g., downtime of a machine) [38]. However, this should not only be limited to the descriptive facts of the event, but also consider the effects on the current production (e.g., a delay in the current production step leads to delayed order completion). Finally, it must be examined for each event whether it impairs or prevents the feasibility of the current schedule ($FR_{dod}9$) [38]. If the current schedule can no longer be fulfilled, the DSS must present corresponding information ($FR_{dod}10$) [38, 40]. In order to avoid continuous and active checking of the system for occurred events by the user, the system should inform the user about the occurrence of an event ($FR_{dod}11$). In this regard, one of the experts said: "*We would see at a stroke whether we have problems with any follow-up orders due to any breakdowns or the slower machine speeds. I receive a pop up saying that there is a need for action. [...] I don't really have to keep an eye on production, I only want to be informed when I have a problem.*" (expert G). Table 2 summarizes the requirements for the detection of deviations.

Table 2. Functional requirements for the detection of deviations

Requirement	*Description*
$FR_{dod}1$-4	Analyze production process data (1), supplier data (2), production data (3), order data (4)
$FR_{dod}5$	Categorize the results
$FR_{dod}6$	Present the identified events
$FR_{dod}7$-8	Determine (7) and present (8) the effects of the identified events
$FR_{dod}9$-10	Check (9) and present (10) the feasibility of the current schedule
$FR_{dod}11$	Notify about detected events

Reacting to deviations represents the core of the support provided by the DSS. In this regard, it is necessary to know all potential reactions and the consequences of the respective reaction, which requires simulating the situations that occur when executing reactive measures. A central element is therefore the creation and execution of alternative schedules ($FR_{rtd}1$) [40, 41]. As described in Section 2, objectives ($FR_{rtd}2$) (e.g., adherence to schedules or minimization of lead times) and priority rules

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($FR_{rtd}3$; e.g., first-in-first-out) [5, 22] must be defined to create a production schedule. In order to be able to create reactive schedules based on the identified events as well, the simulation further requires selecting relevant events. However, since events usually are the starting point of a simulation in the case of reactive rescheduling, it makes sense to only deselect events that are not relevant for a simulation ($FR_{rtd}4$) [34, 41]. It is also necessary to be able to select which measures the system simulates as possible reactions to the events ($FR_{rtd}5$). This is particularly important in order to reduce the simulation time since each measure causes additional iterations [1, 42]. Furthermore, the decision maker should have the possibility to prioritize released orders ($FR_{rtd}6$; e.g., in order to consider particularly relevant customers) [1, 5].

After the simulation is configured as described above the DSS must execute the simulations ($FR_{rtd}7$) [5, 20, 41]. Every simulation represents a combination of selected objectives and priority rules, applied measures, and considered events [5, 41]. The resulting alternative reactions must then be evaluated ($FR_{rtd}8$) and displayed ($FR_{rtd}9$) as well as sortable ($FR_{rtd}10$) and filterable ($FR_{rtd}11$) [19, 20, 41, 42]. The evaluation should take into account the consequences of an alternative in the form of decision-relevant factors such as costs, adherence to schedules, machine utilization, throughput times and risks, in order to make the alternatives and their effects comparable [41, 42].

In addition to displaying the planning alternatives in an overview, the system must offer functionalities to show the individual alternatives in detail ($FR_{rtd}12$). In the respective detailed view of an alternative, the user should also be able to edit the alternative ($FR_{rtd}13$) [43]. In a final step of reacting to deviations, the decision maker has to select a planning alternative, which then becomes operative ($FR_{rtd}14$) [21]. This is particularly important since DSS merely provide a basis for decision making, but do not make decisions themselves. Table 3 summarizes these requirements.

Table 3. Functional requirements for the reaction to deviations

Requirement	*Description*
$FR_{rtd}1$	Create production schedules
$FR_{rtd}2$-3	Define objectives (2) and priority rules (3) for the production schedule
$FR_{rt}4$	Define events not relevant for simulation
$FR_{rtd}5$	Define possible measures to be taken
$FR_{rtd}6$	Prioritize orders
$FR_{rtd}7$	Simulate schedules
$FR_{rtd}8$-11	Assess (8), present (9), sort (10), and filter (11) the alternative production schedules
$FR_{rtd}12$	Show details of the alternative production schedules
$FR_{rtd}13$-14	Edit (13) and select (14) an alternative production schedule

4.3 Design and Development

Since we want to provide a solution applicable in various production scheduling environments regardless of the specific company or industry, we did an abstraction

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step. Thus, prior to implementing our software artifact, we deduced the meta-requirements listed in Table 4 based on the functional requirements.

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Table 4. Functional meta-requirements

representation of the current situation	detection of deviations	reaction to deviations
MR$_{rcs}$1: Functionalities for capturing, processing and aggregating production-relevant data from CPS and connected systems **MR$_{rcs}$2**: Functionalities for manually entering production-relevant data **MR$_{rcs}$3**: Functionalities for displaying current production-relevant data, the current schedule, and the progress of its processing.	**MR$_{dod}$1**: Functionalities for identifying and displaying events in production-relevant data **MR$_{dod}$2**: Functionalities for determining and presenting the resulting effects of the identified events and the associated feasibility of the current schedule. **MR$_{dod}$3**: Functionalities for notifying about the occurrence of events	**MR$_{rtd}$1**: Functionalities for configuring and executing a simulation of alternative reactions **MR$_{rtd}$2**: Functionalities for evaluating and presenting alternative reactions **MR$_{rtd}$3**: Functionalities for editing and selecting alternative reactions

In order to implement the meta-requirements and thus solve the problem described in Subsection 4.1, we developed a responsive web application. This allows the user access via stationary (e.g., desktop PC or notebook) as well as mobile devices (e.g., tablet or smartphone). Hence, our application consists of two components: (1) a server hosting the application, providing interfaces for the CPS integration, and containing the database as well as (2) a web component accessible through a web browser.

We realized the server component using PHP for the application and a relational MySQL database. The database represents the integration component of the DSS since it must also contain the data of all enterprise systems. Such material integration makes sense for use in production scheduling since virtual approaches are unsuitable due to their long runtime [44]. For the client sided web component we applied the Angular framework, since it enables the efficient presentation of dynamic contents. This is recommendable to cope with the real-time data. We further used Arduino Uno-based sensors and actuators to emulate CPS, which continuously collect as well as process real-time data and, in case of a deviation, forward the data to the server component.

The client side is further divided into two views. First, there is a view for the decision maker that presents an overview of the complete production schedule as well as all the corresponding details. Second, we implemented a machine view that shows schedule information for one specific machine (e.g., events or schedule of that machine). On the one hand, this view might serve as a workplace overview shown on a mobile device at the corresponding machine. On the other hand, it offers a possibility to compensate a lack of sensor equipment of a machine, since it enables the user to enter data about the machine manually (e.g., delays or failures).

As we are primarily aiming at providing decision support in production scheduling, we focus on the first view in this paper. Once a decision maker logs in, the system displays a dashboard showing an overview of the current schedule, current events and

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released orders. Figure 2 shows a screenshot of the current schedule. The system further provides detailed information on the complete schedule as well as on all enlisted objects and data like machines, occupancies, events, or orders. If deviations or events occur during production execution (e.g., captured by CPS), the system dynamically displays them in the event overview in real-time and shows a notification if necessary (e.g., if the schedule is not executable anymore). The released order section of the dashboard provides information about the orders and corresponding customers as well as about the real-time progress of those orders and the status of in time fulfillability.

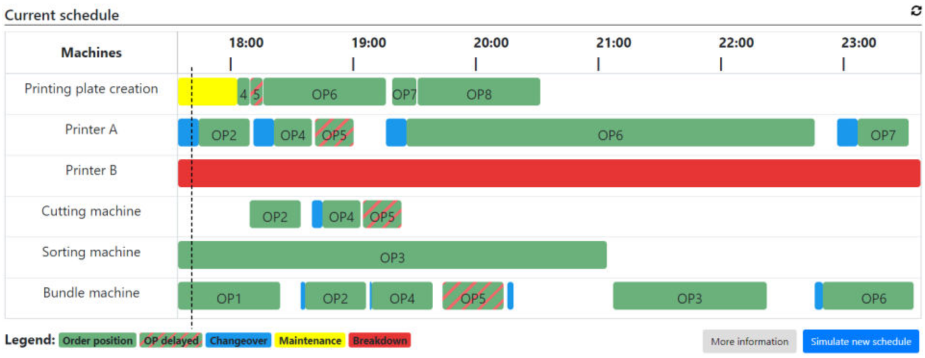

Figure 2. Dashboard of the zEUS application

In the event that rescheduling is necessary, the *zEUS* application offers the possibility of configuring and simulating various possible planning alternatives on the basis of the available real-time data. For all simulated alternatives, the system presents decision-relevant criteria (e.g., costs and processing time) as well as risk and quality assessments (see Figure 3). The risk assessment is based on whether the fulfillment of the plan is endangered, for example, by low buffer times or the plan requires the suspension of necessary maintenance and thus involves a technical risk. The quality assessment represents a weighted aggregation of all decision-relevant criteria. The weighting is done based on the company's objectives (e.g., production as cost-effectively as possible or on schedule as far as possible) via parameters to be defined in the settings.

The decision maker can further view the details of every alternative showing, for example, the resulting schedule, order information, corresponding shifts, employee requirements, and necessary measures. In the details view, it is also possible to edit the schedule, post comments, and accept the alternative. By accepting an alternative, it becomes the new as is schedule and is communicated to all connected devices.

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Alternative production schedules

ID		Priority rule	Objective	Costs [€]	Machine utilization [%]	In time [%]	Overall throughput time	Risk	Assessment	Has comments	Details	
7		VSR	Adherence to schedule	5147.76	39.00	100.00	28h 35min		41	No	Details	Accept
8		VSR	Minimize throughput time	5094.26	37.00	100.00	36h 12min		27	No	Details	Accept
9		VSR	Minimize changeover time	4926.50	38.00	100.00	30h 5min		46	No	Details	Accept

Figure 3. Result overview of the *zEUS* application

4.4 Demonstration

After implementing the artifact, we demonstrated it in a laboratory setting as described in Section 3. For this, we prepared an application scenario for a printing company. This scenario offers a production running according to a suboptimal plan (an order is delayed). In the course of working with the system, CPS-based events (a need for maintenance and a machine breakdown) occur in real-time triggered by sensors. In order to provide comparability, the events do not occur after a certain time but at certain progress stages of the scenario. The test persons should use the system to grasp the present situation and the current as well as occurring events and, in response, identify and implement a better schedule. To ensure this, we formulated concrete tasks (e.g., identify current deviations, simulate and evaluate alternative actions, or reschedule the production). Both a stationary PC for the decision maker view and tablets for the mobile decision maker view and the machine view were used as devices. Overall, this gives the test persons the opportunity to use the DSS in all three application areas (see e.g., Section 4) and evaluate it later on.

4.5 Evaluation

After demonstrating the zEUS application to the test persons, we asked them to fill in a TAM-based questionnaire. We thereby wanted to find out, whether the solution was suitable for the use in the three areas of application and how useful and usable it is.

All of our 48 test persons were able to solve all of the tasks provided by our scenario. Since there were no significant differences between the results of students, research associates, and practitioners, we will consider only overall values below. The evaluation showed that the respondents were able to pass the scenario well with the help of the *zEUS* application (mean: 4.90), consider the use of such a system to be meaningful (mean: 4.96) and would use it if they were a decision maker in production scheduling (mean: 4.92). With regard to the three application areas, the respondents stated that *zEUS* is useful in representing the current situation (mean: 4.85) and detecting deviations (mean: 4.88) as well as in reacting to deviations (mean: 4.90).

With respect to usability, the evaluation showed that although the application was assessed well overall (mean: 4.67) and in the three application areas ($mean_{rcs}$: 4.56, $mean_{dod}$: 4.54, $mean_{rtd}$: 4.54), the surface was initially perceived as partially overloaded. One respondent indicated this in the comment field: "*The surface is overloaded with information. When used for the first time, it seems to be much*

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information. Many possibilities to get detailed information, often it is not quite clear what can be found where." (test person 15) However, other test persons also stated that the system was "*easy to operate and clear after a short orientation period.*" (test person 7)

With regard to the meta-requirements for representing the current situation, our study showed that the respondents obtained the necessary information to grasp the current situation (mean: 4.81). This indicates that the production-relevant data are adequately collected, processed and aggregated ($MR_{rcs}1$). Furthermore, the system displays the data thus determined accordingly ($MR_{rcs}3$). This is underpinned, for example, by the fact that the presentation of the current schedule (mean: 4.92) and the order overview (mean: 4.79) were rated as useful. In addition, the test persons stated that manual data ($MR_{rcs}2$) entry was also possible and helpful (mean: 4.58).

The meta-requirements for the detection of deviations were also addressed. The identification of new events and their presentation in an overview ($MR_{dod}1$) was rated as good (mean: 4.60). The fact that the connected CPS provided events instead of technical values was rated positively as well (mean: 4.79). This also applies to the notification indicating the occurrence of a new event (mean: 4.88; $MR_{dod}3$). Furthermore, the possibility of displaying the effects of the events ($MR_{dod}2$) was rated as good (mean: 4.54). Overall, the test persons stated that they received all necessary information on deviations and events (mean: 4.75).

We also addressed the meta-requirements for reacting to deviations. The study found that configuring and executing simulations ($MR_{rtd}1$) was considered helpful (mean: 4.88). The fact that the evaluation (mean: 4.81) and presentation (mean: 4.67) of the alternative actions are described as useful implies that $MR_{rtd}2$ was implemented as well. Finally, the system offers the possibility to edit the alternatives and to select one of the alternatives ($MR_{rtd}3$). The test persons also describe this as meaningful (mean: 4.69).

In summary, the test persons rated the *zEUS* application as meaningful and useful. Test person 1, a practitioner, stated "[a] *very innovative system with potential*" as additional feedback and test person 7 described the system as "*significantly easier compared to manual planning*". Furthermore, the test persons stated that the inclusion of CPS-based real-time data could keep the impacts of deviations to a minimum (mean: 4.63). Nevertheless, we also received feedback regarding improvements, especially with respect to the usability. In addition, we implemented all meta-requirements for the application and demonstrated that the application is appropriate in our scenario.

5 Discussion and Conclusion

In this paper, we developed a DSS for production scheduling in the context of CPS and thus created a level 1 design science contribution [3] adapting the problem-centered design science research approach of Peffers et al. [4]. Based on an interview study and a literature analysis, we identified practical problems and derived objectives for the solution. On that basis, we inferred requirements and generalized them into

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meta-requirements in order to enable support of production scheduling independent of the production environment. We presented the software artifact *zEUS* as a CPS-based solution, supporting decision makers in production scheduling (RQ1). We presented this solution to practitioners, research associates, and students during the demonstration phase in a laboratory setting. Subsequently, we gathered feedback with a questionnaire in order to evaluate the artifact (RQ2). According to the evaluation, *zEUS* is suitable for the use in our scenario and beneficial in the three areas of application. For example, by including CPS-based real-time data, it enables reacting more quickly to problems during the execution of the schedule and thus keeps the consequences to a minimum. Nevertheless, we have also identified critical points. For example, the user interface is initially perceived as overloaded. Furthermore, the system requires master data and CPS data. Even though this data should exist in every company, they cannot be taken for granted in practice as six of our interview partners stated.

As usual with practice-oriented research, there are limitations: First, we developed a software artifact and only proved its functionality in our application scenario. Secondly, although our test persons all have sufficient background knowledge to assess the solution, only a few of them are actually professionally involved with PPC. The respondents were also limited in their feedback by the questionnaire and, with the exception of the comment fields, could only give a quantitative assessment, but not a detailed statement. Thirdly, our experimental setup consisted of only a small number of CPS. In this respect, there is a lack of knowledge on how well the application can cope with a significantly larger number and range of CPS or with missing and false data. Consequently, additional studies are necessary to address these limitations. Further scenarios and the use under less controlled conditions should be investigated. In these studies, primarily decision makers in production scheduling should be interviewed in qualitative interviews in order to obtain detailed feedback on the functions and usability of the *zEUS* application.

Nevertheless, we developed a software solution that supports new technologies and concepts such as CPS and can improve production processes in companies. This enables companies to meet the ever-increasing demands of their customers and keep pace with their competitors. From a scientific point of view, the meta-requirements also represent a good entry point for a level 2 contribution by identifying design guidelines through extension, application, and evaluation of the system. For this, however, we need to pass a further design science circle in order to generalize the results.

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