Function allocation between humans and systems in self-optimizing production networks

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Abstract

In order to stay competitive in today’s global markets, new forms of production systems are needed to react flexibly to changing market conditions and to meet the customers’ demand for variety. Therefore, within the Cluster of Excellence "Integrative Production Technology for High-Wage Countries" self-optimizing production systems are developed that are able to adapt autonomously to changing product structures and production processes. These self-optimizing systems range from single machines over manufacturing respective assembly cells, up to the factory level within a socio-technical production network. Despite the high level of automation, the human is still an integral part of the system but there is a change in function allocation between humans and systems. Therefore, this paper describes the changing role of the human operator due to self-optimizing systems exemplarily for three processes from the fields of logistics and production planning, assembly and manufacturing. Based on expert analyses the work processes were assessed and modelled in case of self-optimization as well as for the conventional systems. The results showed that independent of the degree of automation self-optimizing systems provoke a shift of the role of the human from mainly sensorimotor tasks to predominantly supervisory control, as the human is only responsible for final decisions or even only has to intervene in case of malfunction. Ergonomic challenges and approaches for a user-oriented automation are exposed in this paper.

Keywords: Self-optimizing production systems; Functional allocation; Socio-technical systems; Task analysis

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1. Introduction

The increasing global competition of today’s markets and the resulting cost pressure require premium quality products and cost-effective high-volume manufacturing which can be satisfied by highly automated production systems. Moreover, the market demands flexible adaptation to changing conditions due to short product life cycles and the customers’ demand for variety. In order to stay competitive, it is crucial for companies in high-wage countries to anticipate customer-specific needs for an individual adaption of high-quality products and to react extremely flexibly. Therefore, ultra-flexible forms of production systems are required to continuously adapt to changing product structures and the corresponding production processes [1]. One approach to achieve a high level of flexibility is to design self-optimizing production systems that are able to autonomously define, reach and sustain optimal operating points. Based on active sensing and monitoring of the environment, these systems possess the ability to adjust their structure, function, and behavior as well as their internal goals autonomously according to perceived changes of the situation and the predicted consequences [2].

Within the Cluster of Excellence "Integrative Production Technology for High-Wage Countries" self-optimizing systems are developed as a part of a socio-technical production network ranging from single machines over manufacturing respective assembly cells, up to the factory level. Despite the high level of automation, these systems will never be able to operate completely autonomously without the human. However, the high level of automation also induces a change of function allocation between humans and systems. The aim of this paper is to describe the changing role of the human operator due to self-optimization and to expose ergonomic challenges for user-oriented automation, which need to be solved in future production systems. Therefore, the allocation of functions between humans and systems within self-optimizing production systems in comparison to conventional systems was investigated. Exemplarily three processes from the fields of logistics and production planning as well as assembly and manufacturing were chosen.

2. Self-optimization in socio-technical work systems

Production networks can be regarded as complex, socio-technical systems consisting of horizontally and vertically interconnected production entities. Within these socio-technical production systems the human has to be considered as an integral part, because the mutual inter-relationship between humans and technical systems is crucial for improving productivity and flexibility. Self-optimization in socio-technical production networks aims at autonomously define, reach and sustain optimal operating points and ranges from single machines over manufacturing respective assembly cells, up to the factory level. This can be described by a self-similar structure of self-optimization for production systems [3], which is depicted in Figure 1. The interpretation of this architecture is as follows [3]:

The numeric (sub-symbolic) information processing of the automatic control systems is represented by the bottom level of the architecture. The adaptation process in the next higher levels is based on “cognitive controllers” on a more abstract level (symbolic). The current system state, in conjunction with the pursued goal, is the basis for the decision-making process. A model of the controlled process is generated and updated in conjunction with the environment within the model builder. This model contains the execution conditions of the production process as well as the information of the interacting subsystems in the appropriate granularity. Based on the model, the optimizer and decision unit are able to make context-sensitive decisions. The machine level realizes, for example, functionalities of a model-based self-optimization [4], whereas the cell level aggregates several machines to higher level production units following coordinated actions. The segment combines several cells for the overall production process and can therefore be considered as a macro structure. Correspondingly, there is an increase of the level of abstraction from process level to segment level. Furthermore, the type of information that is processed changes. The automatic control is based on continuous spatiotemporal signals, whereas the controllers at machine, cell, and segment levels use a symbolic representation of the state information. At each of the higher levels, a human operator interacts with the cognitive controller [5]. This can be a physical interaction or supervisory control tasks processed in order to monitor the system behavior.
Based on external and internal objectives, the optimization criteria of the production system are determined. Constraints regarding the lead time or costs are an example for external objectives, that are processed at each level and transmitted to the next lower system. In addition, each subsystem on the individual levels generates its own internal objectives. At the machine level, this could be constraints regarding wear and tear or energy consumption whereas at higher levels the objectives could relate to, for instance, throughput and utilization. Furthermore, due to the self-optimizing functions, the systems are able to adjust their internal objectives in order to adapt to environmental changes in the production process [4]. As long as the internal objectives do not contradict the external objectives or objectives generated by higher order systems, they can be adjusted and altered by the corresponding cognitive controllers. In this way, systems can generate additional constraints for their subordinated systems.

This self-similar architecture provides a general framework for the application of self-optimization in socio-technical production systems. Further context specific adaptions of self-optimization for production management, manufacturing and assembly systems are detailed in [6].

It becomes clear that self-optimization in socio-technical production networks is principally seen from a technical view. Neither human reasoning nor learning in self-optimizing production systems are represented explicitly in the architecture. In order to present a self-optimizing socio-technical system, both factors –the human and the machine – have to be considered as a jointly optimizing system.

Socio-technical systems can be classified according to their degrees of automation. Sheridan [7] distinguishes 10 levels of automation as depicted in Table 1. Consequently, self-optimization can also occur in different levels of automation, where it can be implemented, for example, to support the human operator by giving him/her different options for his/her action or it can be an almost autonomously working system when considering manufacturing processes. However, for all levels of automation the operator needs to know the system state at all times.
Table 1. Levels of automation due to Sheridan [8].

| Level | Degree of automation |
|-------|----------------------|
| 1     | The computer offers no assistance, human must do it all. |
| 2     | The computer offers a complete set of action alternatives, and … narrows the selection down to a few, or |
| 3     | … suggests one, and |
| 4     | … executes the suggestion if the human approves, or |
| 5     | … allows the human a restricted time to veto before automation execution, or |
| 6     | … executes automatically, then necessarily informs human, or |
| 7     | … informs him after execution only if he asks or |
| 8     | … informs him after execution if it, the computer, decides to. |
| 9     | The computer decides everything and acts autonomously, ignoring the human. |
| 10    | The computer decides everything and acts autonomously, ignoring the human. |

A sub-project of the Cluster of Excellence investigates human-machine interaction in self-optimizing production networks, because socio-technical systems require ergonomic human-machine interfaces to enable the human to recognize the current state of the system and to be able to intervene if necessary. The long-term objective is to enable the human and the system to operate safely and reliably in terms of a socio-technical self-optimizing system. Behaviour patterns of the technical system need to be transparent to the human and the system has to be perceived and accepted as a team-partner. In order to achieve this, the changing function for humans due to self-optimizing systems needs to be analysed in a first step to identify ergonomic challenges that need to be solved to guarantee a safe and reliable socio-technical self-optimizing system.

3. Work processes in self-optimizing production systems

In order to describe the changing function for humans due to self-optimizing systems we investigated the change in function allocation for humans and machines exemplarily for three processes from the fields of logistics and production planning, assembly as well as manufacturing using a detailed task analysis. Based on expert analyses the work processes were analysed, modelled and evaluated in case of self-optimization as well as for the conventional systems using the K3 method [8].

3.1. Logistics and production planning

In conventional order processing processes the main role of the human is to derive recommendations for actions and check the planning suggestions of the system. A simplified description of the process can be given as follows: After an order is initiated by the customer, the system accepts the order and executes the material disposition. Afterwards, the human checks the material disposition and decides if revisions are necessary. If no revisions are needed he releases the disposition. Otherwise, he derives recommendations for action and adjusts the disposition. After that, he releases the disposition and the system executes the production planning. The result is checked by the human regarding options for optimization. If these are necessary, the human derives recommendations for actions, adjusts the production planning, and releases it. If no optimization options can be applied, he releases the planning of the system. Afterwards, the production process is executed by the system.

For self-optimizing order processing processes, a supply chain control room is introduced containing human and system activity. In this case, the system of the supply chain control room derives recommendations for actions for unacceptable supply chain parameters before the material disposition is checked. These recommendations are checked by the human in the supply chain control room and adapted in case of unacceptable parameters. Otherwise, the material disposition is released by the human in the supply chain control room. If the supply chain parameters are permitted, the human in the order processing processes can check the disposition directly. While checking the disposition, the human eventually adapts it and releases it, if it is admissible. If not, the system for the order processing processes has to derive new recommendations, which are checked again by the human. If the release is approved, the system used for the order processing processes starts the production planning and checks for optimization options. If there is any optimization possible, the system derives recommendations for actions. These are checked by the human, eventually adapted and finally released. If not, the system has to derive new recommendations. After the release is approved, the production is executed by the system. Using this self-
optimizing approach the primary activity of the human is to check planning suggestions and recommendations of the system and release them.

An excerpt of the order processing processes is depicted in Figure 2 for the conventional process (a) and for the self-optimizing process (b). It becomes clear that in the conventional process recommendations for actions are derived by the human, whereas in the self-optimizing process the system derives the recommendations and the human only checks it and makes the final decisions.

3.2. Assembly

Conventional frame assembly in aircraft industry is still characterized by a low degree of automation. Frames and skin of the shell are connected by clips. For this assembly at first the frames and skin get positioned with the help of a crane. After that, the clips are placed and preliminary fixed with a rivet gun by the human. The components are transported to a portal rivet plant, which is started by the human to assemble clips and skin. In the meantime, the human monitors the process and intervenes in case of problems. When this assembly of clips and skin is finished, the components are transported to the assembly robot by the human with the help of a transport vehicle. After the human has started the process, the robot assembles the frames and clips. The human is monitoring again the process and intervenes in the case of malfunction. When the robot has finished its work, the components are transported to a post-production station, where missing clips are added and assembled manually by the human.

Fig. 2. Excerpt of the modelled work processes for order processing processes for the conventional process (a) and for the self-optimizing process (b).

Human activity in order processing process | System activity in order processing process
---|---
Check optimization possibilities due to lead time | Execute Production Planning
[no optimization options available] Derive recommendations for action | [optimization options available]
Adjust Planning | Derive recommendations for action | [optimization options available]
Approve Release | [revisions needed] Check recommendations for action | [no revisions needed]
Execute Production | Adjust recommendations | Approve Release | Execute Production

a b
For self-optimization of this process multiple systems for simulation of deformation, measurement of the component positions and positioning and deformation of the components are added. After initial clamping of the components by the human, the human starts the automatic process of assembly. Component position and deformation, which is caused by exertion of a defined force on the component by the deformation and positioning system, are measured in multiple iterations by the system in order to find parameters for the simulation of deformation. Once the parameters are identified by the system of deformation simulation and no disturbance occurred, the simulation is started and the system for positioning and deformation places the clips at their target position. If the position of the clips differs from their target positions, all steps from the beginning of the simulation are repeated. Otherwise, the assembling robot starts the assembly of the skin and clips. If no disturbance occurs, the robot executes tool changing for the frame assembly. The robot places the frame, whose position is checked by the measurement system. If all frames are placed correctly, the automatic process is finished. During the autonomous assembly, the human observes and corrects occurring disturbances. Using self-optimization the tasks of observation and monitoring are of increasing importance and require knowledge about the process.

3.3. Manufacturing

As an example for manufacturing we analyzed, how the adoption of self-optimization to the weaving process changes the socio-technical system. In conventional weaving processes the scaffolding process is dominated by tasks executed by the human. The human sets the basic parameters known from his experience and starts the weaving process via the machine interface. At the same time the weaving machine executes the trial, the human monitors the process. In case that the machine reports a malfunction, the human resolves the problem manually and restarts the process. After a specific time, the human decides to stop the machine and takes a sample. The sample is tested by the human with respect to quality. Based on his experience he either changes parameters and restarts the process to create another sample or, if the sample suffices the criteria the weaving process is started and monitored by the human in the further process.

By the application of self-optimization to the weaving process the function allocation changes for the scaffolding process. In this case, the human sets the basic parameters via the machine interface. In addition he needs to define quality factors for the modelling systems. If a model already exists, it is used by the optimizing systems to execute the optimizing process and set the machine parameter to the optimal operating point. After that, the weaving process is directly started. If no model exists, the human defines the experimental space and starts the modelling system and the weaving process. The modelling system develops the experimental design and starts the experiment. From this point the different technical systems control further steps as setting the operating points prior defined by the modelling system, monitoring the current state, recording the measurements and eventually adjust the experimental design. When this iterative process of model building is completed the optimizing systems executes the optimizing process and sets the machine parameter to the optimal operating point. During this model building and optimizing activities the human monitors the process and, in case of a malfunction, he needs to resolve the problem and restart the process.

4. Effects on the human due to changes in function allocation

All exemplary processes show independent of the degree of automation that self-optimization provokes a shift of the role of the human from mainly sensorimotor tasks to predominantly supervisory control, as the human is only responsible for final decisions or only has to intervene in case of malfunction. However, the results also show that even if the human is not fulfilling sensorimotor tasks permanently in self-optimizing systems, he still needs to be in the loop to be able to intervene properly. Hence, sensorimotor skills are still important. Furthermore, the human needs to have a mental model about the ongoing-process. Consequently, the requested knowledge about signal processing, methods of automatic control and optimization algorithms increases. The human has to have high system knowledge that include for example understanding about system interrelationships and supply chains. This results in different demands on qualification.

Besides the changes in required competencies, the strain profiles that are evoked within the human are also different. Due to the change from sensorimotor tasks to predominantly supervisory control, strain profiles are shifted
from primary physical strain to primary mental strain. Whereas physical strenuous tasks are reduced by highly automated self-optimizing systems, mental demands are significantly larger. The difference in the amount of workload resulting from monitoring tasks, which generally go along with low workload, and intervening tasks, which can lead to very high workload, leads to temporal inhomogeneous mental strain profiles. Moreover, due to the high degree of autonomy, the human operator is confronted with many unexpected behaviour patterns, that can also lead to high mental strain.

5. Future challenges and approaches

The results show that in self-optimizing systems the human is often not directly in the control loop anymore, because he/she is only monitoring the process. Therefore, a distance between the human and the ongoing process is created. The contradicting point is that the operator needs to intervene in case of malfunction and therefore needs to have a detailed knowledge about the current state of the system. Therefore, it needs to be ensured that the human has an appropriate good mental model about the system state at all times. This can be achieved by keeping the human in the loop even for tasks that are executed by the system autonomously. This comprises, for example, also the adjustment of internal goals. If the human is not informed about these changes within the systems, he cannot react adequately to upcoming problems. Hence, information about the system state and activity needs to be provided and visualized ergonomically so that the operator is able to understand it.

The challenges for making automation a team player postulated by [9] also apply for self-optimizing production systems. The aspect that the behavior of the team partners needs to be predictable has already been addressed. Moreover, it is important to mention that the team partners need to have a common understanding of the current state. That means that the system should inform the human about any irregularities already before a problem occurs. That enhances the operator’s attention and he is already informed about the current state in case of intervention. The operator’s situation awareness is typically lower for supervisory control than for executive tasks, so that another challenge is to present information about the current state of the system in a way that attracts the operator’s attention. A possible approach could be the integration of simulations to the monitoring process or the use of a method in that the operator needs to answer questions about the current state of the system.

A question that arises from the example for logistics and production planning is how to enhance the operator’s trust in the recommendations for action given by the system and at the same time promote a critical review of it before approving it. The quantity and quality of information that is needed to support decision making needs to be investigated individually for each self-optimizing support system, because the final decision is still performed by the human. Lastly, new qualification concepts and systems need to be developed to address the change in method expertise which is needed to apply the technical knowledge. Given different operators of different ages with different knowledge levels, such a concept needs to be designed adaptive for different target groups.

6. Conclusion

Based on three self-optimizing processes from different levels of socio-technical production networks we described the change of function allocation in comparison to the conventional processes. We were able to identify that for all investigated processes self-optimization leads to a shift of the role of the human from sensorimotor tasks to predominantly monitoring tasks as the human is only responsible for final decisions or even only has to intervene in case of malfunction. The ergonomic challenges for a user-oriented automation that were derived from the analyses show that there is a need to develop not only the technical aspects for self-optimizing systems but also consider the human already in the developing process in order to achieve a safe and robust socio-technical system. At the same time new qualification concepts need to be established to meet the changing requirements of the tasks.
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