Preprints of the
16th IFAC Symposium on Information Control Problems in Manufacturing
Bergamo, Italy. June 11-13, 2018

Human-centred Adaptation and Task Distribution utilizing Levels of Automation

Xiaoli Chen*, Michael Bojko*, Ralph Riedel*,
Konstantinos C. Apostolakis, Dimitris Zarpalas**, Petros Daras****

** Department of Factory Planning and Factory Management, Chemnitz University of Technology, Chemnitz, Germany (Tel: 0049-371 531-34686; e-mail: xiaoli.chen@mb.tu-chemnitz.de)*

*** Information Technologies Institute, Centre for Research and Technology Hellas, Thessaloniki, Greece (Tel: 0030-2310 464160; e-mail: kapostol@iti.gr)*

Abstract:

Considered as one of the key enablers of smart factories, human-machine adaptation and improved task distribution plays an important role for the realization of effectiveness, efficiency and satisfaction of factory staff. In this paper, with a view to the researches and practices related to the common results of automation adaptation, existing approaches have been revealed as being too general to be put into practice, or being focused too detailed on one industry and therefore cannot be imposed in others. With this in mind, an applicable concept is developed for the setup of an adaptation system, which stems from the EU funded Factory2Fit research project. Within the proposed concept, production automation levels are captured and defined to adapt to the skills and experience of the user. An adaptation engine with human-centered automation is further designed. Based on this, a demonstrator with the scenario of an automobile supplier company is established, which helps to validate the approach proposed within the paper.

Keywords: Adaptation System, Adaptation Engine, Human-centered, Level of Automation, Smart Factory, Automated Manufacturing Systems, Flexible Automation, Intelligent Manufacturing Systems

1. INTRODUCTION

Considered as a top priority of industrial development, Industry 4.0 has being highlighted as the pursuit of both academia and practice in companies (Chen et al., 2018). For the implementation of Industry 4.0, a smart factory is seen as one of the three key enablers (Kagermann, Wahlster and Helbig, 2013). In smart factories, the designing and performing of tasks will follow the aim to fit well for different skills, capabilities and preferences of workers. This is also the purpose of our project: Factory2Fit – Empowering and participatory adaptation of factory automation to fit for workers. Factory2Fit is a research and innovation project under the European funds of Horizon 2020. One of the aims of Factory2Fit is to realize continuous adaptation of work conditions with changing levels of automation in evolving production systems. According to the project, the adaptation of automation is highly required to contribute to continuous human-automation collaboration. This also helps current and forthcoming employees to develop their competences to become smart, satisfied and knowledge-embodied workers for future factories. There is no doubt about the importance of automation adaptation to upgrade competitiveness of companies. However, one of the arising questions is: How to realize automation adaptation within a production environment? Derived questions that should be answered are:

- What is automation adaptation?
- Which factors should be taken into account when setting up an automation adaptation system?
- How to establish an automation adaptation system?
- How to maintain the established adaptation system, so as to keep effectiveness, efficiency and satisfaction of factory staff?

An automation adaptation system is an approach established to capture on-going work conditions, and then to realize dynamic distribution of task responsibility between the human operator and the machine (Hilburn, 2017). For the achievement of automation adaptation, many factors should be taken into account. These are real conditions regarding Context of Use (CoU) as the background (Maguire, 2001); interface systems as the media; automation adaptation engines as the tools; and reliability, efficiency and human satisfaction as the output. Many issues should also be clear when designing and implementing this kind of adaptive systems (Hilburn, 2017). They are related to the identification of CoU elements, setup of triggering logic/rules based on the on-going conditions, determination of control algorithms, and so on.

With all these in mind, the purpose of this work is to provide an approach, which helps to setup a human-machine adaptation system. General work begins with the introduction of the background. Further work also goes on with the composition and function of an adaptive automation system, which attempts to shed some light on the possible solutions for the realization of an adaptive automation system. Moreover, a demonstrator is described for the validation on the architecture and framework of the system. Experiences with regards to the application of adaptation system in different cases are also discussed and concluded as in the end of this paper.

2. AUTOMATION ADAPTATION SYSTEM

2.1 Theoretical basis

In this work, we see automation adaptation as one of the major aims of the research in human-machine interaction. Within this scope, three mainstreams can be found in the pertinent studies. They are: 1) Identification of the key implementation factors, which have potential influence on the performance of human-machine collaboration (Charalambous et al., 2013). Here, individual and organizational factors are both included, where individual issues refer to trust in automation, mental workload, loss of situational awareness, skill degradation, automation-induced complacency, and also stress, anxiety and safety due to human-machine collaboration. While the organizational factors involve communication with the workforce, training and development of the workforce, formation of a multi-disciplinary team, worker involvement in the implementation, identification of a process champion, organizational flexibility and top management commitment. 2) Setup of an architecture for the interaction between human and machine (Miller and Parasuraman, 2003; Bruni et al., 2007; Oxstrand et al., 2013). Here, a taxonomy of the human-machine collaboration has been clarified (Miller and Parasuraman, 2003); and the theoretical framework for the support of optimal interaction between humans and automated systems has also been designed (Bruni et al., 2007; Oxstrand et al., 2013). 3) Outlining requirements for an effective human-machine interaction. The factors concluded within these works can be used for the evaluation on the performance of interactive and adaptive activities (Joe et al., 2014). Taken together, all of the above works contribute to the idea of our study, yet one major shortcoming can still be found: though separate issues have been abounded, very little systematic theory can be found. Interrelationships among influence factors, decision on the choice of human-machine interaction styles, and the expected performance are even less covered. Besides, these approaches (e.g. Bruni et al., 2007; Oxstrand et al., 2013) have also been revealed as being too general to be put into practice, or being focused too detailed on one particular industry (e.g. air traffic in Aricò et al., 2016) and therefore are not being able to be imposed in others. Therefore, a systematic applicable concept is highly required for the setup of an adaptation system.

2.2 Automation Adaptation and Types of Automation

Automation is the ‘full or partial replacement of a function previously carried out by the human operator’ (Parasuraman et al., 2000, p. 287). It is a manner related to how a task should be carried out. To provide on-going decision support on when and to which degree a task should be automated, an automation adaptation system is needed, as it is a promising approach to assign the workload/tasks with an appropriate manner. That is, suitable tasks should be conducted by suitable operators (human and/or machine) within suitable time. This helps to enhance the overall performance and reliability of the system (Hilburn, 2017). Within a production system, tasks could be divided into routine tasks and adaptation tasks. Different types of adaptation exist depending on the contents of task within the production system themselves (seen as in Fig.1).

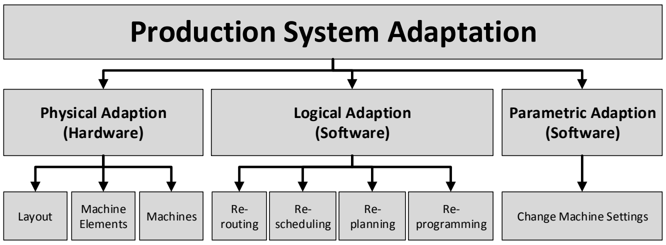

Fig. 1. Adaptation fields within the production system (Based on Järvenpää et al., 2016)

With a view to the adaptation tasks listed in Fig. 1, detailed roles can be defined based on the specific requirements of the task, where they are supposed to be implemented by human and/or machine. Therefore, we see that the types of automation are in high relation to the manner of human-machine interaction. Taken together, and based on the work of Frohm et al. (2008), the item ‘automation’ has been divided into physical-related and control-related, where physical-related automation is based on the technical level of physical tasks, e.g. carrying out a task manually or with help of single machine unit or with help of multi-functional units of equipment and so on. On the contrary, control-related automation is related to cognitive processes in which control activities are intended to be automated. They are more suitable for the realization of logical and parametric adaptation tasks as shown in Fig. 1. Considering the functional aspect of the tasks, control-related automation further can be detailed as automation of ***data collection***, ***data processing***, ***decision making*** and ***task implementation***.

Within a production system, control-related decisions are more highlighted as the concern of the analysis. As on one hand, current tasks within the shop floor are mostly cognitive-related ones. On the other hand, though the influence of soft factors gets increasingly important, seldom norms or industry standards can be found as reference to deal with control-related issues. Moreover, within the production system, the subject of control is information, and information is intangible but hard to obtain. Certain technologies (such as sensor networks, radio-frequency identification techniques, etc.) are required for collecting the necessary information. All these reduce the complexity of studying control related decisions. Therefore, with the attempts to shed some light on the possible solutions for the realization of an adaptation automation system, control-related adaptation is encouraged to be emphasized as the concern. Additionally, the concept and approach developed from the analysis of control-related adaptation can also be transferred to the physical-related ones.

2.3 Levels of Automation and Setup of a human- centred Adaptation Systems

Working on the Levels of Automation (LoA) is the foundation for designing an automation adaptation system, as it helps to deal with the decisions on 'to which degree tasks should be automated' Considering Frohm (2005, p. 107), LoA could be understood as the "amount of technique and information provided to the operator in order to know what, how and when to do a specific task in the most efficient way". Reliability and efficiency are highlighted as the pursuit of the automation analysis here (Chavaillaz et al., 2016). Safety is another emphasis when defining the automation level used in the field (Maguire, 2001). All these are highly concerned as in the previous researches. However, very less attention has been paid to the satisfaction of humans, though it is really important to keep the motivation and positive emotions of the employee, so they contribute their knowledge and trigger their creative ideas on how to carry out their work. Therefore, a ***human-centered*** adaptation system is highly required to be considered when designing an automation adaptation system. In the following stage, based on specific skills, capabilities and preferences of users, and with the consideration of available LoA, a ***human-centered*** automation adaptation system would be established.

2.4 Setting up a human- centred Adaptation System

Based on the foregoing analysis, a general framework has been constructed, which aims to develop a human-centered adaptation system with a systematic way (seen as in Fig. 2).

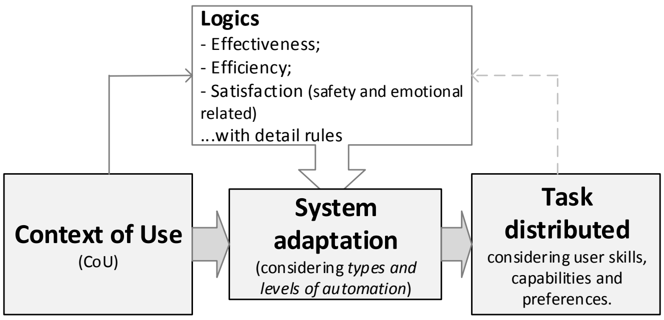

Fig. 2. General Framework for the adaptation system

The whole system initiates from the holistic analysis of the CoU. Here, CoU is interpreted as a profile which records all related characteristics of users, machine conditions, tasks, and the physical and social environments in which the tasks are carried out (Maguire, 2001). Here, besides factors suggested within others' work (Maguire, 2001), the interpretation of CoU is more focused on including parameters of workers. This refers not only to physical aspects, but also to capabilities, preferences and cultural aspects. All these composed as a user system, which services as a database and contributes to an improved adaptation of the human-machine interactions. In the end, higher satisfaction concerning emotional state and safety of factory staff is achievable. With the current conditions of the CoU as input, a set of specific logics with detailed rules would be used for the matching between dynamic situations of the adapted system and the choice on the adaptation levels. This includes not only the choice of automation types, but also the suggested LoA. All these outputs will be reflected on the manners how tasks will be distributed between human and machine.

The target of the adaptation system is to keep and increase performance of the work. Satisfaction of the factory staff is another intent of the described system. Therefore, rules considering effectiveness, efficiency and satisfaction will be used not only for the matching of CoU to the choice of automation, but also for the optimization of the adaptation system. Taken together, the concept of the adaptation engine has further been composed as in Fig.3.

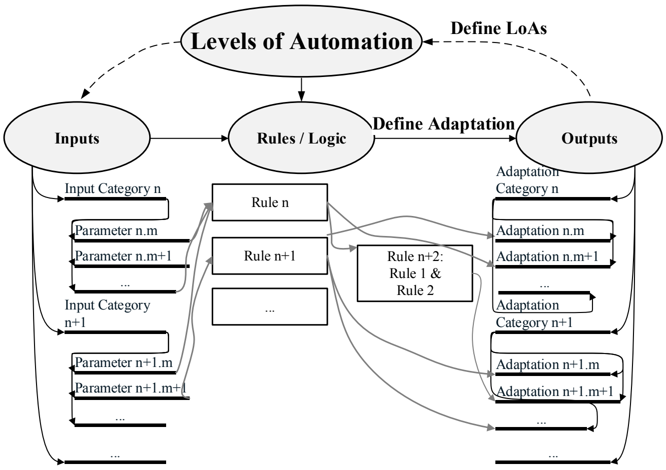

Fig. 3. Concept of the automation adaptation system

As shown in Fig. 3, we see that for the setup of an adaptation system, the general logic of the concept follows the logic of input-rules-output. Here, components concluded from the CoU serve as the ***input of the system***. And the setup of the ***logic*** triggers the adaptations with the consideration of effectiveness, efficiency, emotional- and safety-related satisfaction. In addition, ***outputs of the engine*** consist of a selection of automation types and automation levels. In this work, types of automation are sorted based on ***automation for data collection***, ***data processing***, ***decision making*** and ***task implementation.*** And according to Parasuraman et al. (2000), ten levels of automation will be used to describe the automation levels here. They are gradually changing from total manually to full automation. In detail, LoA have been listed as in Table 1.

Table 1. Descriptions of automation levels

Level	Description
Level 1	The computer offers no assistance, human must take all decisions and actions.
Level 2	The computer offers a complete set of decision/action alternatives.
Level 3	Narrows the selection down to a few choices.
Level 4	Suggests one alternative.
Level 5	Executes the suggestion if the human approves.
Level 6	Allows the human a restricted time to veto before automatic execution.

Level	Description
Level 7	Executes automatically, then necessarily informs the human. When error occurs, can reject further actions and inform human for correction.
Level 8	Informs the human only if asked. When error occurs, can reject further actions and inform human for correction.
Level 9	Informs the human only if the computer decides to. When error occurs, gives the information to human and the performance could be corrected while operating.
Level 10	The computer decides everything, acts autonomously. Errors could be anticipated and the actions could be adjusted to avoid an error. When the problem cannot be avoided, gives inform to human beforehand.

3. DEMONSTRATOR FOR VALIDATION

To orchestrate the matching of LoAs to workers effectively, the aforementioned methodology has been implemented in an Automation-Level Adaptation Engine. Within this engine, an appropriate matching of workers to tasks/processes should be determined firstly. With using a capability-based matching method (Järvenpää et al., 2016), parameters of resources could be matched to the specific requirements of process when considering about the needed capabilities and detailed reasoning. With the input from a *Capability Editor*, the module is responsible for defining a Resource Ontology. Moreover, with the help of a *Pre-process Plan Generator*, the process parameters can also be defined.

With the existence of a *pre-process plan*, tasks can be interpreted regarding the required capabilities. With the consideration of related requirements, the decision-making process mainly refers to the matching of aforementioned workers to the tasks designated in the *pre-process plan*. Following with this logics, each task is designated with a number of LoAs. And when considering the preferences of candidates who could be assigned to the task, appropriate LoA would be adapted automatically. This helps to bring the different aims of effectiveness, efficiency with work-related satisfaction (emotional- and also safety related satisfaction) of the workers together.

3.1 Scenario for demonstration

The pilot for the study for automation adaptation is located at an internal factory measurement laboratory. The workers there are mainly operators or technicians. Each worker is registered in a so called skill matrix. Within this matrix, the specific knowledge and skills required for the existing roles are documented. Thus, this kind of matrix could be considered as an input for the Resource Ontology through the Capability Editor. With the measurement laboratories, the measurement tasks and related subtasks for the execution of a measurement order, would be defined. All these are through the Pre-process Plan Generator. And the personal limitations or preferences of the workers could be added to the Ontology by the workers themselves. Therefore, the preference of workers would automatically be considered by the decision support for system adaptation.

3.2 Modelling of the system

As mentioned, matching of workers to tasks requires input from a pre-process plan. An ordered graph of processes that acts as a recipe for turning raw material into the finished product or part has been composed (Järvenpää et al., 2016). Within this graph, LoAs can be defined as "Profiles" of these processes and tasks. This describes all possible ways in which processes can be performed in terms of different LoAs that are defined for each type of automation. These include automation related data collection, data processing, decision making, and task implementation (See example in Fig. 4).

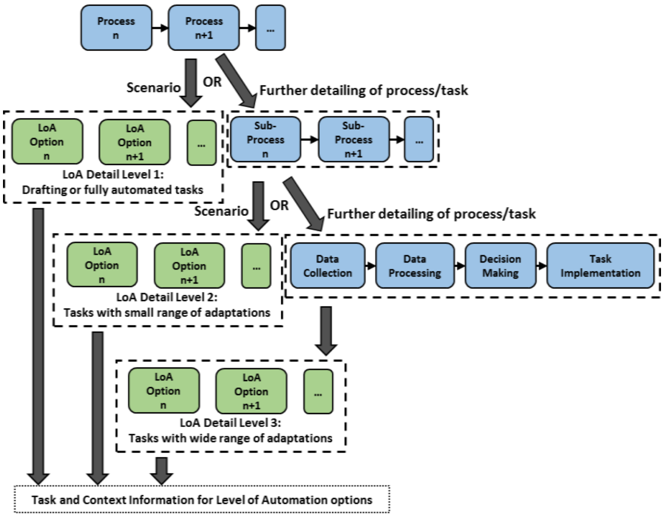

Fig. 4. Description and definition of levels of automation

As shown in Fig. 4, differences between processes and LoA profiles are: processes contain information about the requirements to perform a process. Therefore, based on the interpretation of capabilities and resources, parameters of processes could be used to select appropriate resources. This is also what Järvenpää et al. (2016) have implemented in their work. On the other hand, a LoA profile includes the information for control-related adaptation. In other words, it contains a specific "weak" capability (called "Preference"). This kind of capability can be assigned to the characteristics of workers with the parameters, such as "preferred User Interface font size". This capability triggers a similar matching technique between the requirement set and the appropriate control-related LoA parameters. Here, requirement set refers to the worker's preferences for carrying out a specific process. In this way, LoAs are matched to workers, who are matched to the processes in the first place respectively.

In short, the LoA matching approach works as follows:

1) Workers are matched to processes. Process characteristics become requirements. Rules (Logics) are being generated for these requirements. The system finds the most appropriate workers for each process in the pre-process plan.

2) LoA profiles for the processes are matched to workers. “Preferences” characteristics of each worker become requirements. Rules (Logics) are being generated for these new requirements in a similar fashion as for matching workers to processes. The system finds appropriate LoAs for the worker. This helps to achieve maximum perceived satisfaction for these processes.

3.2 Engine designed for the demonstration

The Automation Level Adaptation Engine first identifies the workers, who possess adequate capabilities for each process in the pre-process plan. This initial fit is supported by performing a coarse matching of the workers’ capabilities together with the so called *Required Capabilities* list. As a result, a list of workers retrieved from the Resource Ontology has been generated. This is named as *resource pool*. Once the resource pool has been filled with content from the Resource Ontology, rules are automatically generated for each process parameter specified in the pre-process plan. Rules will be:

1. Specify the parameter name to look for elements, which are currently in the resource pool. Reserved keywords (such as min or max) will further designate the type of comparison.
2. Specify the value constraint against which the matching parameter value of each element in the resource pool needs to be matched.
3. Specify the units (if applicable) for the above described comparison.

The above list represents the rule *Requirement*. Furthermore, each rule is characterized by the following variables:

- Rule *Condition*: Either *true* or *false*, depending on the comparison outcome.
- Rule *Confidence*: Either *0.0* or *1.0*, depending on whether the rule parameter name to look for can be matched to a parameter name of a capability assigned to a resource in the resource pool. If a matching parameter name is found, the rule confidence is 1.0.

All rules will then be stored in a list, namely ruleset. The matching algorithm will then utilize the ruleset and resource pool as input. And the output would be ProcessID/WorkerID sets, which represent workers who satisfy the constraints defined by each rule for a specific process. The process is repeated until all rules have been examined.

After generating TaskID/WorkerID sets for each process in the pre-process plan, a similar matching process is followed to match LoA profiles of processes to their matching workers. In this respect, the TaskIDs with LoA profiles are isolated into a list of tasks with LoAs. The matching workers from the resource pool are also isolated to a list of workers assigned to Tasks with LoAs. The matching process follows a similar procedure to the one described previously, with the notable exception of the worker preferences capability being used to generate a new set of rules. An example of this matching for the demonstrator scenario can be seen below.

Here a worker with a preferences capability, in which the parameter User Interface (UI) Font Size is set to Normal, will generate a new rule as described in the following example.

Rule Requirement
--- Parameter to match: UI Font Size
--- (Optional) Type of comparison: stringmatch (lowercase)
--- Parameter value: Normal
--- Parameter units: -
Rule Condition: False
Rule Confidence: 0.0

The rule requirement specifies LoA profiles to be considered should match the worker’s “Preferences” capability parameter by looking for a matching string. The rule is then initialized with condition *false* and a confidence set to *0.0*.

With the rule specified, the algorithm checks the LoA profiles of each task which result from the list of tasks with LoAs, and looks for the capability “Preferences” parameter “UI Font Size”. If the Parameter is found, the rule confidence is set to *1.0*. In this case, the actual rule requirement is tested to ensure the current LoA is actually suitable in accordance to the worker’s preferences. In this case, the LoA profile’s parameter value for “UI Font Size” is compared against the rule requirement parameter value using a string matching function. The requirement units are employed to convert resource parameter value accordingly to match the rule requirement metric system (none, in our example case). The LoA profile successfully passes the test if its parameter value equals “Normal”. In this case, the rule condition is set to *true*.

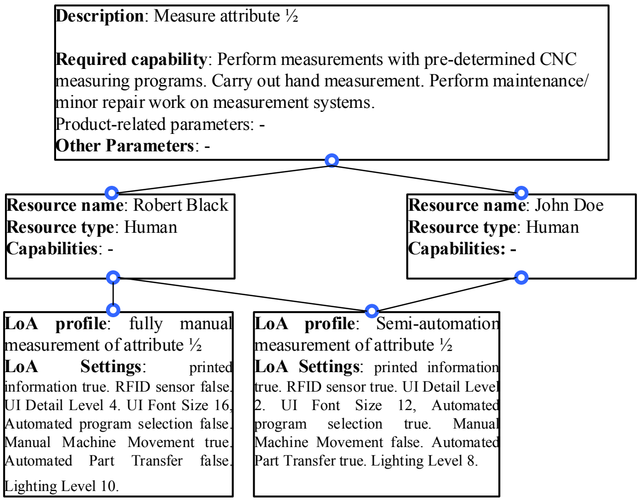

Fig. 5. Example of Automation-Level Adaptation Engine

If the rule confidence is equal to 1.0 and the Rule condition is true, an integer requirements_met parameter kept for every LoA profile is incremented by 1. This additional information accumulates the number of worker “Preferences” being adequately satisfied by a specific LoA profile. After all rules and LoA profiles have been tested, the worker is matched to the LoA profile with the highest requirements_met value. If more than one LoA profiles are matched, the system suggests appropriately links the worker with each LoA profile in a Visual Graph Editor, as shown in Fig. 5. This assists supervisors in determining the proper LoA for a specific task, as more versatile workers can be paired with more strictly preferenced workers in case a process requires more than one assignees, in which case the Automation Level Adaptation Engine suggests the LoA profile best suited for all candidate assignees involved.

4. DISCUSSION AND CONCLUSION

Considering the importance of human-machine adaptation and the improved task distribution for the realization of smart factories, an applicable concept for the setup of an adaptation system was developed. In detail, automation types and LoA have been captured and defined to adapt to skills and preferences of workers. Here, the characteristics of humans have been emphasized for the interpretation on the CoUs, and the satisfaction of humans has been highlighted as one of the key logics of system design. This helps to promote the motivation and trigger the potentials of workers. Moreover, with the structure of input-rules-output, a general concept of an automation adaptation system was designed in a systematic manner. In general, the approach designed and presented in this paper provides a good theoretical foundation for the adaptation in all cases and environments. A more individualized design considering the particularities of a given work situation can further be achieved by specifying the relative factors of input, rules and output. In this paper, the scenario of an automobile supplier company was described for the validation of the approach. For further work, additional scenarios within different industries will be considered for a more broad and sound validation of the concept. When it is well validated, more general results for the application of system adaptation and task distribution within different industries could be derived.

ACKNOWLEDGEMENT

The Factory2Fit project has received funding from Horizon 2020 (H2020/2014-2020), the European Union’s Programme for Research and Innovation under grant agreement n° 723277.

REFERENCES

Aricò, P., Borghini, G., Flumeri, G.D., Colosimo, A., Bonelli, S., Golfetti, A., Pozzi, S., Imbert, J.P., Granger, J., Granger, G., Benhacene, R., and Babiloni, F. (2016). Adaptive automation triggered by EEG-Based mental workload index: a passive brain-computer interface application in realistic air traffic control environment. *Frontiers in Human Neuoscience*, volume 10, pp. 1-13.

Bruni, S., Marquez, J. J., Brzezinski, A., Nehme, C., and Boussemart, Y. (2007). Introducing a Human-Automation Collaboration Taxonomy (HACT) in Command and Control Decision-Support Systems. In: *12^TH ICCRTS “Adapting C2 to the 21st Century”*, pp. 2-13, Cambridge, UK.

Charalambous, G., Flectcher, S., and Webb, P. (2013). Human-automation collaboration in manufacturing: identifying key implementation factors. *Contemporary Ergonomics and Human Factors 2013: Proceedings of the international conference on Ergonomics & Human Factors 2013 (edited by Anderson, M.*), pp. 59-66. Cambridge, UK.

Chavaillaz, A., Wastell, D., and Sauer J. (2016). System Reliability, performance and trust in adaptable automation. *Applied Ergonomics*, volume 52, pp. 333-342.

Chen, X.L., Müller, E., and Riedel, R. (2017). Challenges and Requirements for the Application of Industry 4.0: A Special Insight with the Usage of Cyber-Physical System. *Chinese Journal of Mechanical Engineering*, volume (30), Issue 5, pp. 1050-1057.

Frohm, J, Lindstroem, V., Winroth, M., and Stahre, J. (2008). Levels of Automation in Manufacturing. *Robotics and Computer-Integrated Manufacturing* 47, pp. 53-60

Frohm, J., Lindström, V., and Bellgran, M. (2005). A model for parallel levels of automation within manufacturing. In: *proceeding of the 18th international conference on Production research*, Fisciano, Italy.

Hilburn, B. (2017). Dynamic decision making: the impact of adaptive automation on mental workload. In: *Engineering Psychology and Cognitive Ergonomics (edited by Harris, D.),* pp. 193-195. Routledge, Oxfordshire, UK.

Järvenpää, E., Lanz, M., & Tuokko, R. (2016). Application of a capability-based adaptation methodology to a small-size production system. International Journal of Manufacturing Technology and Management, 30(1/2), 67.

Joe, J.C., O’Hara, J., Medema, H.D., and Oxstrand, J.H. (2014). Identifying requirements for effective human-automation teamwork. In: *Probabilistic safety assessment and management PSAM 12*, Honoluli, Hawaii, USA.

Kagermann, H., Wahlster, W., and Heibig, J. (2013). Recommendations for implementing the strategic initiative Industrie 4.0. *Final Report of the Industrie 4.0 Working Group*, Frankfort, Germany.

Maguire, M. (2001). Context of use within usability activities. *International journal of human-computer studies*, volume 55, pp. 453-483.

Miller, C. A., and Parasuraman, R. (2003). Beyond levels of automation: An architecture for more flexible human-automation collaboration. In: *Proceeding of the human factors and Ergonomics society annual meeting*, Volume: 47 issue: 1, pp.182-186, Denver, USA.

Oxstrand, J., Blanc, K.L., Joe, J.C., Whaley, A.P., Medema, H., and O’Hara J. (2013). Framework for human-automation collaboration: conclusions from four studies. *Technical Report from Idaho National Laboratory (INL)*, pp. 1-95, USA.

Parasuraman, R., Sheridan, T.B., and Wickens, C.D. (2000). A model for types and levels of human interaction with automation. *IEEE Systems, Man, and Cybernetics Society,* pp. 286 – 297.