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of
the 3rd Annual SMACC Research Seminar 2018

Jussi Aaltonen, Simo-Pekka Leino, Kari T. Koskinen & Johannes Hyrynen (eds.)

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FOREWORD

The Annual SMACC Research Seminar is a forum for researchers from VTT Technical Research Centre of Finland Ltd, Tampere University of Technology (TUT) and industry to present their research in the area of smart machines and manufacturing. The 3rd seminar is held in 8th of October 2018 in Tampere, Finland.

The objective of the seminar is to publish results of the research to wider audiences and to offer researchers a forum to discuss their research and to find common research interests and new research ideas.

Smart Machines and Manufacturing Competence Centre – SMACC is joint strategic alliance of VTT Ltd and TUT in the area of intelligent machines and manufacturing. SMACC offers unique services for SME`s in the field of machinery and manufacturing – key features are rapid solutions, cutting-edge research expertise and extensive partnership networks. SMACC is promoting digitalization in mechanical engineering and making scientific research with domestic and international partners in several different topics (www.smacc.fi).

Tampere 25th of January, 2019

Editors

1. LOW-LEVEL CONTROL ARCHITECTURE IN UX-1

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ABSTRACT

This paper describe the low-level mechatronic architecture of the UX-1 robot (Figure 1). In brief, the UX-1 is designed and developed to operate in flooded mine channels that is inaccessible for human. The restricted channel pit of 100 cm in diameter and 50-bar pressure are the condition of robot operating environment [1]. Therefore, UX-1 is design and manufactured to integrate multiple sensors and control unit in small size 60 cm ⌀ sphere [2]. The list of navigation sensors and instrumentation for the purpose of mapping environment and collecting geological data is added to table 1.

Keywords—Underwater robot, Motion control, AUV design

INTRODUCTION

Requirements of operating under 50 bar for 5 hours autonomously lead to design ballast, propulsion and pendulum system to be able to control the robot in the restrict workspace of flooded mine [3]. Following in the paper, low-level control units and protocols to control propulsion, ballast and pendulum system are described. In fact, Power consumption is the crucial factor on the operation of ballast or propulsion unit [4] and efficiency in propulsion or ballast system operation is the determining factor on the length of the mission due to limited power source available on board.

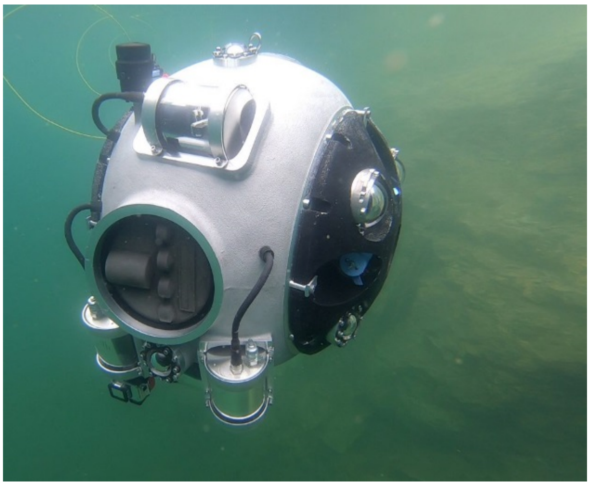

Figure 1: First prototype UX-1

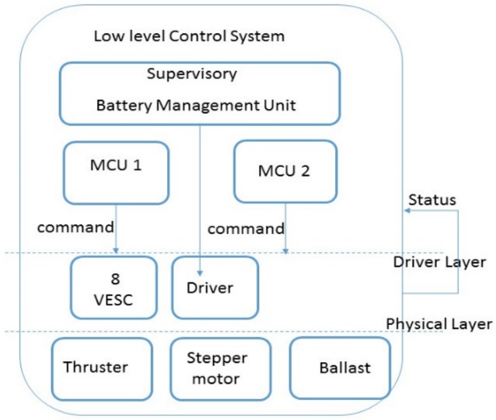

Figure 2: low-level control architecture

The autonomous under water (AUV) UX-1 is equipped with 4 thrusters and 4 speed controller in each side of the sphere, which will be explain later by detail. The distribution and orientation of the thrusters vertically and horizontally determined the degree of freedom and maximum speed of the robot (0.5 m/s). Figure 2 demonstrates the low-level mechatronic architecture [5]; the robot is equipped with ballast system for long distance heave motion while the pitch angle will be controlled by swinging a mass of 6 kg from equilibrium point to +/-100 angle by a stepper motor. On the other hand, two microcontrollers handle the processing of sending command and receiving feedback in the CAN bus. Moreover, for the safety purposes the power consumption of each components will be monetarized through battery management unit.

Table 1: navigation and instrument list

Sonar
Multispectral camera
Laser scanners
Acoustic cameras
UV and SLS imaging units
Sub-bottom profiler
Water sampler
Magnetic field measuring unit
Conductivity and pH measuring units

BATTERY MANAGEMENT SYSTEM

In terms of safety and survival of the system, since the operating work space of the robot is harsh, there are multiple factors that might effect on robot that cause the mission remain unaccomplished. In terms of robot physical malfunction during the mission under water, there might not be exact method to distinguish the cause behind the malfunction.

For instance a failure might happen in one of thrusters due to some particles penetration and preventing the propeller to rotate, in this situation the only possible feedback is detection of a change in velocity or an abnormal change in current value. (If the error originate from communication or control algorithms in low level control system then the error can be detected by velocity feedback and can be addressed by resetting the VESC, however if the error originate from operating workspace then the error must be detected with velocity feedback and current monitoring). Therefore, not only the velocity feedback from VESC is necessary but also the current consumption of every thruster must be monitored.

Due to the former, a battery management system is set up to monitor the current of all low and high-level components including thrusters and vision sensor and instruments (figure 3 demonstrates the detail control architecture).

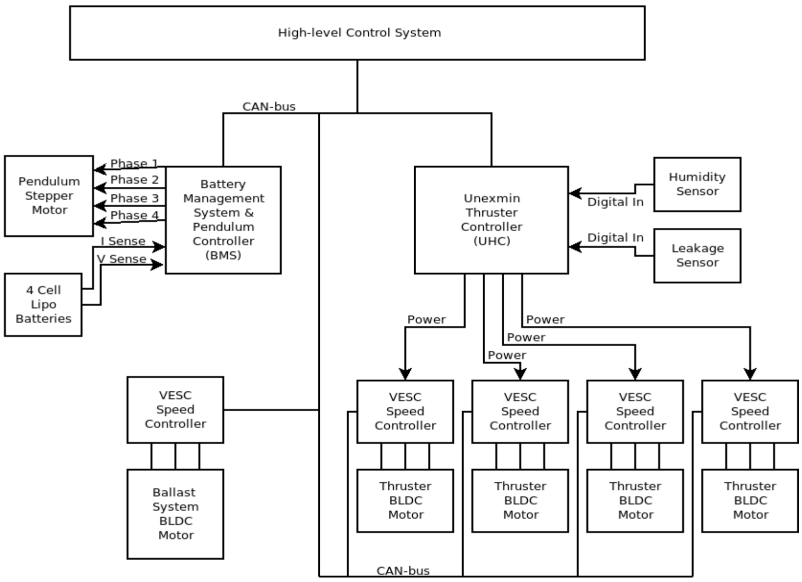

Figure 3: Battery management system

There are several industrial communication protocol field buses that supports topologies like star and ring network. Either of topologies can connect multiple components, however there were several factors such as distance between components, network layout and product availability which lead us to choose CAN bus over ProfiNet, Ethercat, Powerlink, etc. On the other hand, the CAN bus is installed with minimum amount of wiring to decrease the weight of total wires in robot.

There are number of nodes in the low level control unit, the table below demonstrate the components and number data bytes through which they communicate in the CAN bus. The CAN bus networks among all low-level components of the system, this includes 8 VESC and control driver for pendulum system and ballast unit and it extend to battery management unit and IMU.

The advantage of the CAN protocol in UX-1 is the safety in operating the low-level control algorithm and the easy integration of drivers and sensors.

The operation of low-level components are also verified beforehand during hardware in loop implementation where actual thrusters connected to main computer via CAN bus protocol. The Speedgoat use Matlab simulink library and therefore basic control algorithms were develop in Matlab for the purpose testing the actual hardware. This includes VESC, thrusters and sensors such as IMU.

The ready-made device drivers facilitates the interchange between different communication protocol. The hardware in loop implementation phase enabled us to verify the configuration of propulsion unit and its feasibility to operate. To set the command for each VESC, the 4 bytes of electric RPM (EPRM) sends every 200 ms although there are different control command signal that can be also used to control the VESC such as duty cycle. In return, the VESC feedback in every 2ms consists of 4 bytes of EPRM, 2 bytes of current and 2 bytes of duty cycle. The CAN bus is set up to operate at 500kBaud/s. Furthermore every MCU send a status message of 8 byte to higher level control in every 200 ms and the battery management system also propagates 16 byte status message every 200 ms. Therefore, in total there are 36340 bytes per second data transfer in low level control system.

CONCLUSION

This paper attempt to demonstrate the low-level control architecture design of an underwater robotic vehicle. The paper also addresses the hardware layout, communication and protocol interfaces. This work serves as foundation for higher-level control, decision-making and mission specification at later stage.

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2. BENEFITS, ADVANTAGES, ADDED VALUES & ENABLED BUSINESS OPPORTUNITIES THROUGH DIGITAL TWINS, DIGITAL TWIN PLATFORMS AND DIGITAL THREADS

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ABSTRACT

There is an obvious hype going on around Digital Twins, but at the same time the concept is still forming and there are many open question, both technical and business oriented. In this study, we are introducing and presenting some of the enabled benefits, advantages, added values & enabled business opportunities through Digital Twins, Digital Twin platforms and digital threads.

INTRODUCTION

Management of digital data and information flow between many stakeholders and applications as well as interaction between virtual and real world are the backbone of a Digital Twin (DT). Still, it is somewhat unclear what are the true benefits, advantages, added values & enabled business opportunities enabled by DTs. Moreover, we will take into account the perspectives of DTs, DT platforms and digital threads. First, it is essential to understand what is meant by a DTs. A formal definition of a DT is given in [1]: "The Digital Twin is a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level. At its optimum, any information that could be obtained from inspecting a physical manufactured product can be obtained from its Digital Twin." Moreover, it is given also in [1] that: "…digital information would be a "twin" of the information that was embedded within the physical system itself and be linked with that physical system through the entire lifecycle of the system." Thus, our interpretation is: a DT is a multiphysical & multiscale virtual model of a component, product, system and/or process, which is connected to real world by ways of data through its entire lifecycle. Additionally, it is also essential to understand what is meant by a DT platform. Our general definition for a DT platform is: a DT platform is a group of digital technologies that are used for data management and information flow in DTs to create the added value and competitive advantage. Finally, our definition for a digital thread is: a digital thread is a connected data flow and aggregated data throughout whole lifecycle across otherwise siloed product lifecycle management (PLM) functionalities. It is worthwhile to notice that by taking the definitions of a DT and a digital thread into account, a DT platform needs to be a modular, hierarchical, open, unrestricted and versatile solution for PLM with capabilities to manage DT data and information. Still, it is essential to notice that a DT platform is not just a PLM solution. This distinction is represented in Figure 1. With the definitions of a DT, a DT platform and a digital thread, we will now introduce some of the enabled benefits, advantages, added values & enabled business opportunities in prototype, manufacturing and operating phases. Finally, we will present some of the unused potential of the DT concept. It is emphasized that the presented benefits and advantages do not compose a full view of these maturing & evolving research subjects.

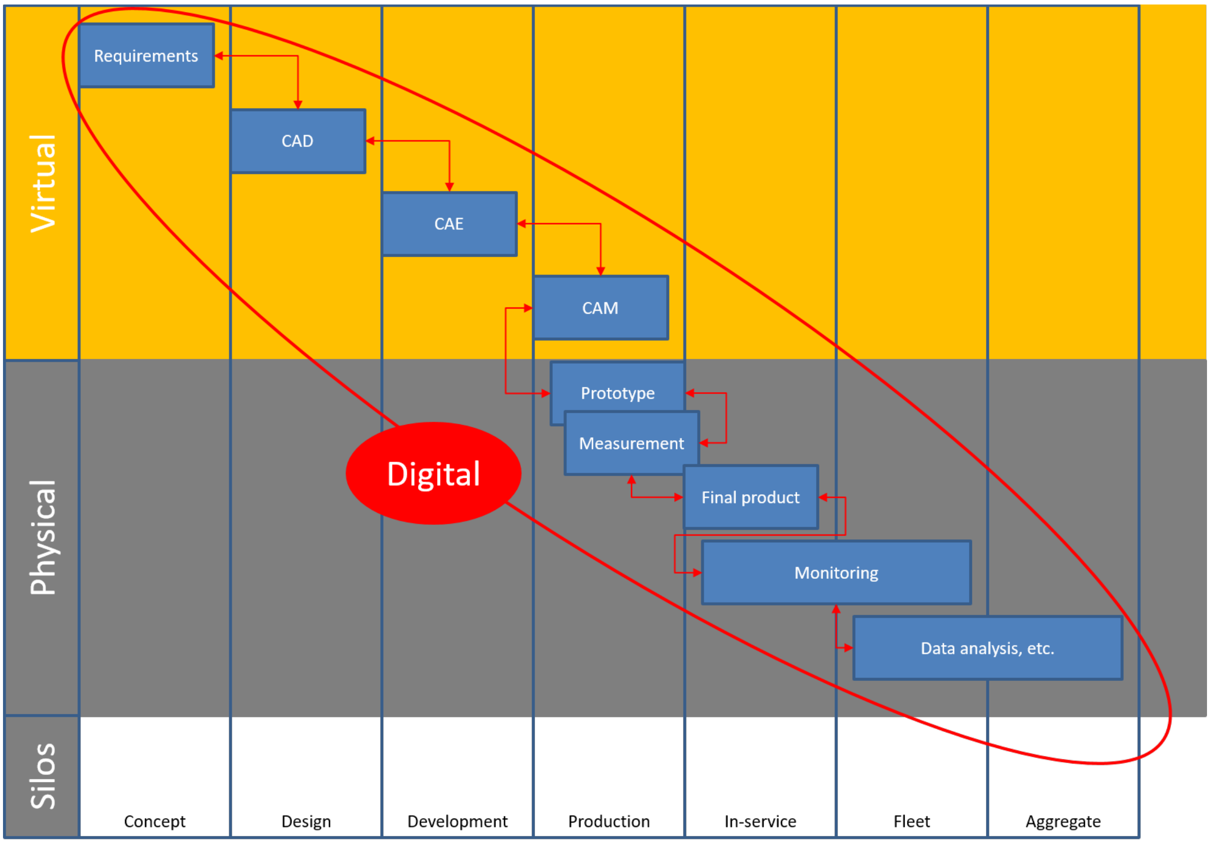

Figure 1: PLM vs. DT platform. A typical PLM pipeline is presented as blue boxes while a DT platform should be based on integrated data management structure over virtual and real worlds in digitalized form.

PROTOTYPE PHASE

A key element of the Digital Twin prototype (DTP, i.e. DT in a virtual prototype phase) is the possibility to explore the design space for different design & engineering solutions, i.e. solutions for common and complex problems, well in advantage before actual manufacturing process. The main objective is to investigate multiple & extreme scenarios to minimize unpredicted undesirable behaviour of the physical twin (PT, i.e. the real world counterpart of the DT) and predict the behaviour in general, i.e. e.g. to enable safe and undamaged operation.

The DTPs allow virtual testing, evaluation and analysis, thus the virtual validation happens much faster and cheaper. Therefore, physical prototypes are not necessarily needed. Due to fact that the DTPs are used before the manufacturing process, they can be used for virtual commissioning. Some authorities e.g. accept computation results as a proof for use permissions, which dramatically shortens time to market and reduce the costs. Same benefits apply also for the normal commissioning procedures, while the essential cost savings are due to reduced number of expensive physical prototypes.

Since the DTPs should be complete descriptions of the PTs (according our definition of a DT), they can be used for optimization purposes. If knowledge of different engineering disciplines is connected in the DTPs, multiphysical & multiscale problems can be solved. For example, decisions can be taken in complex environments whereby the DTPs enable to optimize processes, control virtually every aspect of the full environment, and thus realize benefits in advance. Optimisation applies at least to operability, manufacturability and sustainability.

One of the most popular use cases of the DTPs is in operational training, i.e. e.g. in interactive real-time simulators with motion platforms. Training on operation by using the DTP before put into real operation is made possible with no risk of physical harm to people or machinery and no additional costs from the machine wear or fuel expenses [2]. The DT as a training simulator can dramatically shorten the training period and enable productivity earlier. On the other hand, integrating the DT in real operation enable online operator assistance with analysed severity information of the operation. This reduces potential machinery failures and excessive wear due to overload caused by the incorrect or faulty operation.

MANUFACTURING PHASE

A brief introduction to the DTs in manufacturing can found in [3]. The DTPs makes it possible to manufacture extremely high quality products, since a virtual manufacturing process replaces the construction of expensive prototypes. The virtual model and all potentially imaginable realities and extreme conditions can then be tested and optimized. This extensive process guarantees the production of a sophisticated, first-rate quality before the actual physical manufacture. Moreover, the same process reduces manufacturing costs, increases throughput of the production lines, ensure safe manufacturing, enables design changes to production lines, and enable training for new manufacturing processes. Thus, clear benefits can achieved in manufacturing process management (MPM) and manufacturing operations management (MOM).

It is claimed that simulation of product usage and manufacturing process using the DTP is key driver in asset-intensive industries. Use cases around running production lines in manufacturing will rapidly emerge, and the DTPs are used to justify investments. Another aspect to the DTPs is the possibility to simulate also software within the products. In these cases application of the DTPs can e.g. dramatically change the way manufacturers provide services for industries since the software-hardware integration can be tested before manufacturing.

The objective with the DTP usage in manufacturing isn’t to replace people but rather enhance their capabilities and create new processes to which the people can add value, Still, the inevitable consequence can be seen as reduced labour costs.

OPERATING PHASE

The DT in operating phase accompanies the PT during its entire lifecycle, i.e. the virtual and the real world instances of the same problem are connected. The connection is usually done with measurement data allowing the implementation of predictive maintenance. The DT analyses information given by the PT and uses it to determine when maintenance is necessary based on use and wear and tear. This helps to avoid expensive and unexpected repairs since identification of potential failure is made faster and cost effectively by using the DTs, while the service business is made possible and more profitable. The detailed aggregated information of use, wear, tear, maintenance and performance in technical level enables to offer assets as services, i.e. e.g. product as a service.

The added values enabled by the DTs and provided by the predictive maintenance can be seen as extended lifetime of equipment and assets, and reduced operating costs. If warranty issues can be solved with reliable evidence of the actual usage due to operational profile identification enabled by the DTs, reduced overall costs can be achieved. Additionally, if reliable evidence of the actual operational loading profile can be gathered, it could be e.g. possible to apply reliefs e.g. to classification regulations. Moreover, when the same feedback information from the PT is connected also to the DTP, i.e. to design & engineering, e.g. optimization of the actual performance of the PT utilizing virtual simulation feedback is made possible. The remarkable benefit in these cases could be e.g. due to fact that the actual operational environment and loading profile data and information are used in design & engineering - not the nominal estimates of the operational environment and loading profile. Thus, the DTs are connecting typically disconnected building blocks in engineering silos. Moreover, interconnections enable platform economy in various levels: e.g. each of the DT and DT platform functionalities can be performed separately and integrate the end results into platform. When essential lifecycle information is made possible and available, also the principles of circular economy can be followed more easily. With the aggregated information over the lifecycle consumer insights, customer behaviour data and preferences can be gathered. This makes possible to improve products and assets, and develop new products in a more customer- and data-driven way. For example, utilization of customer data in engineering will inevitably lead to customer process optimization. Thus, the overall effect comes into reach and services with new ways of product innovation.

UNUSED POTENTIAL

Quite of often data and information from the PT and the DT exist, but not the data nor the information are not exploited fully. Therefore the DTs are enabling data capitalization, since the DTs are connecting engineering knowledge to business knowledge via enabling technologies such as IT, IoT, data analytics, AI, etc. The major reason for industry to realize more value from the DTs is that the DTs can connect with the digital thread. With the digital thread, tremendous insight into functionalities (such as design & engineering, business, etc.) can be acquired. The ability to virtually see and understand why something is happening is a big competitive advantage. By studying the DTs, engineers can determine the root cause of any performance problems, improve output, schedule predictive maintenance, evaluate different control strategies and otherwise work to optimize performance — and minimize operating expenses — in near real time. Therefore, the DTs with the situation awareness capabilities are the key enabling functionalities also for developing autonomous systems, machines and vehicles, and enhanced automation. Thus, DTs, DT platforms, digital threads and their integration will support development towards next industry renewal, i.e. Industry 4.0, and beyond. Still, as concluded in [4], DT technologies are maturing and finding their way into specific industrial applications where there is a clear business case and return of investment (ROI).

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3. INTELLIGENT PRODUCTION TECHNOLOGIES: IMPROVING COMPARATIVE EVALUATION OF POTENTIAL INVESTMENTS IN AUTOMATION, ROBOTS, COBOTS, AND HUMAN INTELLIGENCE AMPLIFICATION/AUGMENTATION

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ABSTRACT

Production technologies that include some artificial intelligence (AI) can be described as intelligent production technologies. AI is being incorporated into automation, robots, cobots, devices for amplifying/augmenting human intelligence, smart tooling, smart materials, etc. Many established techniques are available to support the evaluation of potential investments in intelligent production technologies. These include: traditional capital investment appraisal techniques (CIAT) such as Return on Investment; adjusted CIATs that encompass intangible benefits; CIATs for investment options characterized by uncertainty, such as Real Options Analysis; and investment evaluation techniques derived from performance management tools such as the Balanced Scorecard. Despite the wide scope of established CIATs, the comparative evaluation of intelligent production technologies remains challenging. For example, there are reports of global companies experiencing poor outcomes because of overestimating the relevance of some intelligent production technologies to their operations. Here, an overview is provided of how comparative evaluation of intelligent production technologies can be improved. In particular, through quantitative measurement of the comparative complexity / simplicity of work for different types of intelligent production technologies; and through debiasing human decision making about alternative investment options. These two improvements address current gaps in industrial economics and behavioural economics that limit the usefulness of existing CIATs.

INTRODUCTION

Bad investment decisions are being made about intelligent production technologies (IPT) despite the availability of many established techniques to support their evaluation (Charette, 2018; Gibbs, 2018; 2016; Harbour and Scemama, 2017). These include: traditional capital investment appraisal techniques (CIAT) such as Return on Investment; adjusted CIATs that encompass intangible benefits; CIATs for investment options characterized by uncertainty, such as Real Options Analysis; and investment evaluation techniques derived from performance management tools such as the Balanced Scorecard. In this short paper, an overview is provided of how comparative evaluation of IPT can be improved. In the next section, need and method are set-out for quantitative measurement of the comparative complexity / simplicity of work for different types of intelligent production technologies. Then, need and method are set-out for debiasing human decision making about alternative investment options. In the concluding section, these two improvements are related to existing CIATs.

QUANTITATIVE MEASUREMENT OF COMPARATIVE WORK COMPLEXITY / SIMPLICITY

Detailed measurement of production processes is essential to the management of production processes (Groover, 2007). The need for quantatitive measurement of comparative work complexity / simplicity for different types of intelligent production technologies is illustrated by examples of the very costly consequences of bad investment decisions. For example, one car maker invested 10 million euros in new technology that would install windshields on cars on the assembly line. Then, it turned out that maintaining the new production technology required twice as many workers as the company had previously employed installing the windshields (Harbour and Scemama, 2017). Such problems can extend to many production tasks. For example, one global car maker has replaced assembly robots with human workers. This is because the assembly robots were not well-matched to the assembly tasks that they had been bought in to do (Gibbs, 2016). Bad investment decision can even encompass all of production. For example, investments in automation at Tesla slowed down production. So, its costly investment in automation was removed from its factory (Gibbs, 2018). Moreover, even when investments in intelligent production technologies continue to be used, they can cause production defects that are more difficult to identify that conventional human errors, while having much more costly consequences than conventional human errors (Charette, 2018).

An essential first step in measuring the comparative complexity / simplicity of work for different types of IPT is to apply an appropriate measure. For example, physical components can be measured in terms of dimensions, tolerances, and life-cycle criteria. However, these are not appropriate for measuring the comparative complexity / simplicity of work in terms that are applicable to both artificial intelligence and natural intelligence. By contrast, situated entropy is an appropriate measure. Situated entropy is larger when there is a larger number of ways in which something can happen at a workplace. For example, there is entropy of 2.58 if a physical component in production work can be fitted in six different ways with equal probability: compared to entropy of 1.00 if the component can be fitted in two different ways with equal probability. Production work can include: discrete equal entropy, discrete unequal entropy, joint entropy, conditional entropy, and differential entropy. These different types of entropy are relevant to different types of work involving different types of intelligent production technologies. It is important to note, that IPT can simplify some aspects of production work for some types of workers, while introducing higher levels of situated entropy for other types of workers. For example, more colorful presentation of production information may only increase situated entropy for robots. By contrast, more colorful presentation of production information may increase human cognitive absorption and reduce situated entropy for human workers. As summarized in Figure 1, quantitative measurement of situated entropy is incorporated into a six-step methodology for getting the best out of investments in intelligent production technologies. Extensive details about measuring comparative complexity / simplicity in terms of situated entropy in different types of factory work can be read in Fox, 2018 and Fox et al., 2018.

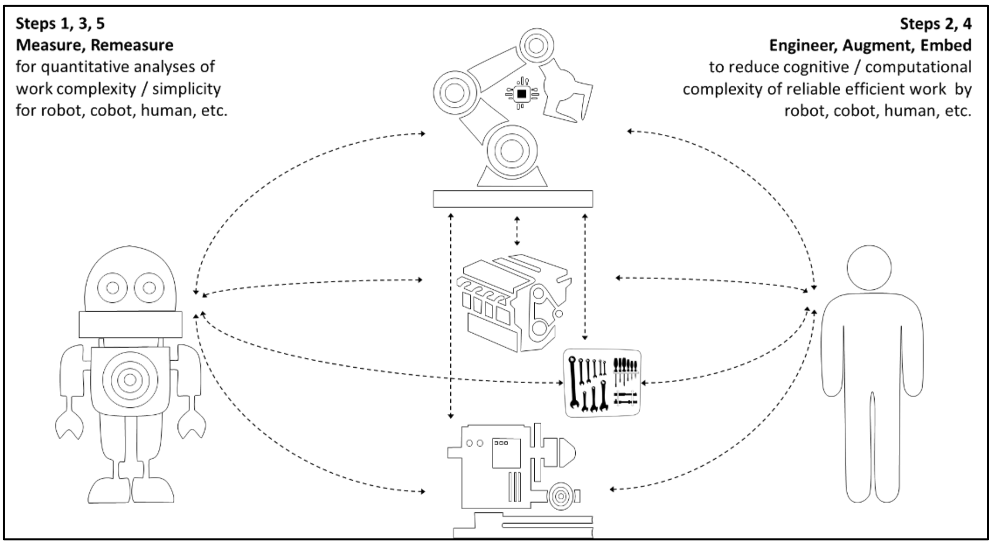

Figure 1 Quantitative measurement of situated entropy as part of a six-step methodology

DEBIASING HUMAN DECISION-MAKING ABOUT ALTERNATIVE INVESTMENT OPTIONS

Bias in human decision-making about alternative investment options can arise from unconscious human preferences for least cognitive effort and subconscious human preference for least social resistance. These can coincide in biases related to fads, hype, lock-ins, path dependencies, success traps, and groupthink. Fads can involve extensive marketing by management consultants, which suggests that the ideas in fads are panaceas. Having started out on a path based on a fad, ideas about the best course of action to take can become path dependent - even when better options become available. Technology hype can also lead to unoriginal ideas about what is the best course of action to take. This happens when hype draws attention to potential positive effects, while excluding or under emphasising a new technology's dependencies on other factors and its potential negative effects. Lock-in can follow investment in a particular fad, hype, and/or path because of beliefs that there has already been too much invested to quit. In addition to the external influences of fads and hype on forming original ideas about what directions to follow, path dependency and lock-in can arise from success traps. These involve a period of successful organizational performance leading to stale ideas about what makes success for all time into the future. Common across fads, path dependencies, hype, lock-ins, and success traps can be groupthink. Such biases can lead to three types of errors. Inept positive perceptions (Type III error) can lead to expensive distractions that can arise, for example, when decision-makers focus upon what have formerly been winning factors after they have become only qualifying factors. False negative perceptions (Type II error) can lead to missed opportunities, for example, when decision-makers ignore alternatives to dependencies and lock-ins. False positive perceptions (Type I error) can lead to futile investments, for example, when decision-makers overvalue fads, hype and previous successes (Fox, 2015).

It has been reported that companies that implement procedures for debiasing business decision-making achieve marked performance improvements (Baer et al., 2017). Various techniques can be applied in debiasing. Firstly, biases can be made explicit through representations, such as the cartoons shown in Figure 2 that highlight the absurdity of making expensive investment decisions based on fads, hype, success traps, etc. Next, counterfactual reasoning can be applied to counteract biases. A counterfactual statement is an expression of what has not happened but could happen under differing conditions. For example, what could happen if the path dependencies, lock-ins, etc., are ignored by taking alternative courses of actions. Then, positive priming can be achieved by making reference to actual cases where organizations have made successful investments based on their own original thinking rather than biases. Subsequently, original thinking can be facilitated through what can be described as the distant-association view of ideation, which is based on the proposition that creativity relies on making associations that are distant from prevailing conceptualizations. After that, ideas about what investments to make in intelligent production technologies can be reviewed through structured self-questioning, which takes into account multiple perspectives simultaneously. These perspectives should include divergent timeframes and multi-layered explanation of causation (Fox, 2016; 2013; 2008).

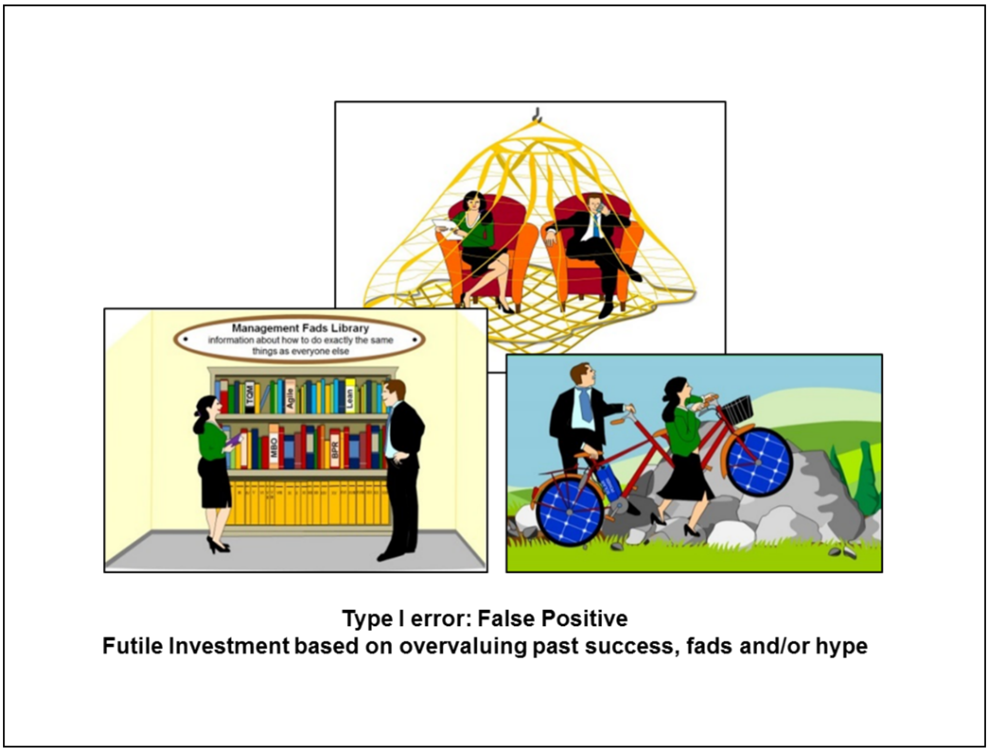

Figure 2: Debias by making explicit the absurdity of basing investment decisions on biases

CONCLUSIONS

Despite the wide scope of established capital investment appraisal techniques (CIAT), the comparative evaluation of intelligent production technologies remains challenging. In this short paper, an overview is provided of how comparative evaluation of intelligent production technologies can be improved. First, through quantitative measurement of the comparative complexity / simplicity of work for different types of intelligent production technologies. This can be achieved with precision through application of multiple measures of different types of situated entropy including discrete, joint, conditional, and differential. Second, through debiasing human decision making about alternative investment options with a variety of interrelated techniques including counterfactual reasoning, positive priming, distant-association view, and structured self-questioning. The usefulness of existing CIAT for evaluating potential investments in intelligent production technologies can be improved by early stage input of quantitative measurements and later stage review of decision options with debiasing techniques.

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4. DIMENSIONAL ANALYSIS CONCEPTUAL MODELING (DACM) FRAMEWORK: PROBABILISTIC SIMULATION USING BAYESIAN NETWORKS

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ABSTRACT

Dimensional Analysis Conceptual Modeling (DACM) aims at modeling the complex systems. The models developed in DACM, are the combination of the causal graph and the list of governing equations. DACM seeks to provide qualitative and quantitative simulation to the models. However, the early development of the framework was limited to enabling qualitative simulation and contradiction analysis to the model using mathematical machinery. This article aims at introducing an approach to transfer DACM models to the probabilistic simulation using Bayesian Networks. This model can also be used in combination with the deterministic of probabilistic methods to explore the interaction of variables in the system qualitatively. The current paper briefly overviews the DACM framework and then explains the steps to extend the DACM model into a probabilistic model, i.e. a Bayesian model.

DIMENSIONAL ANALYSIS CONCEPTUAL MODELING FRAMEWORK

This section introduces Dimensional Analysis Conceptual Modeling (DACM) Framework and briefly discuss its sequence modeling steps and associated theories. The Framework was initially developed as a specification and verification approach to design and model complex systems in systems engineering [1]. It integrates several theories and methodologies related to engineering design, modeling, and simulation. The Framework offers a systematic modeling procedure to establish the causality among the variables describing the system's behavior. It provides the qualitative and quantitative simulation capabilities to models. Figure 4 illustrates the modeling steps of their associated theories integrated into the Framework. The modeling starts with a definition of the system's border and model's objectives. Function modeling represents the sequence of functions that take place in the system under investigation. This step is followed by assigning variables to the functional model. DACM applies the causal rules and color patterns in order to extract the colored causal graph among the system's variables. In the next step, the system's behavioral equations are established by applying dimensional analysis principles to the causal graph. The primary result of this modeling is a colored hypergraph and a list of governing equations. This model is used further for qualitative or quantitative simulations and contradictions detection. Interested readers are invited to get detailed information about DACM Framework and case studies from the authors' published articles [2]–[5].

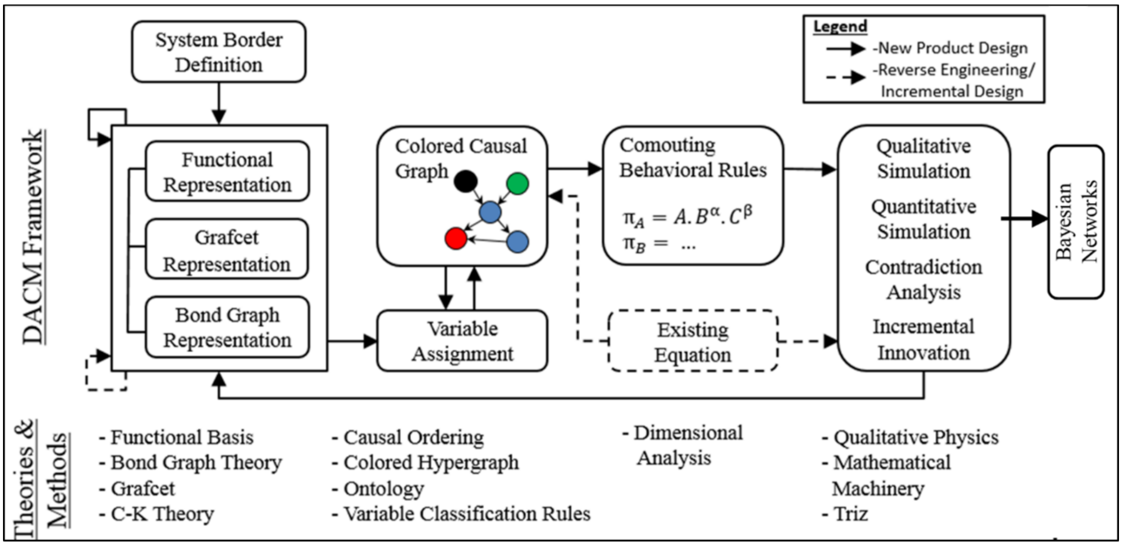

Figure 4 Modeling steps in DACM Framework

TRANSFORMING DACM BAYESIAN NETWORKS

DACM enables modeling the dependencies between the variables describing a system or phenomena that take place in a manufacturing process. Each of these variables has a domain in which they can take values. The variables and their associated range of values form the domain space to explore. Domain space is a space with a dimension equal to the number of independent variables. This means that an increase in the number of independent variables and their associated domain interval lead to increase the complexity of the space to explore. In the design phase, this domain should be explored to find a suitable combination of variables for the system under design/investigation to perfume in the desired way. On the other hand, designers may have preferences and consideration for choosing the values for the independent variables. These preferences can be captured from the experts' knowledge in that domain, which is hard to model, or the designer may simply have some consideration that is not included in the model. Therefore, some values in the domain of each variable can have a more significant preference to be chosen over the other values.

A Bayesian network is a probabilistic model, which can show a combination of qualitative and quantitative aspects of a system in a single model. The qualitative part is a Directed Acyclic Graph (DAG) that depicts dependency and independency relations between variables of the system [6]. The quantitative part has two aspects. One aspect is the nature of variables regarding being a continuous variable, or a categorical or discrete variable. The other aspect of the quantitative part is the local conditional probability tables related to each variable, which is a factorization of the joint probability distribution of the variables in the system [7].

Bayesian networks can handle both the design space and the probabilities behind the choices of values for variables. The causal graph resulted from the DACM framework is used as the DAG for a Bayesian network. Independent variables' domains are divided into several intervals, and the preference of designers is modeled as probability tables for each interval in Bayesian networks. The preference of designers for independent variables' intervals are then collected through a probability assessment process, for example, the Analytical Hierarchy Process (AHP). The mathematical equations and dimensionless numbers used in DACM are a means to find the Conditional Probability Tables (CPTs) for the dependent variables and performance variables.

Once the model is created and validated, it can be used for both prognosis and diagnosis purposes. In prognosis, the probability that a performance variable takes the values in its intervals is calculated based on the intervals of values chosen for the independent variables. It predicts the possible effect of choosing a specific value interval for independent variables of the performance variables. Since the probabilities of independent variables are based on the expert knowledge, the model enhances the designers to know what are the most relevant values to choose for the variables. On the other side of the spectrum, in diagnosis, the probability of all intervals of the independent variables are inferred, for a specific determined interval of performance variable. This can be used when designers need to choose the correct combination of variables, in order to have the performance variables in a design domain.

CONCLUSION AND PERSPECTIVE

This paper briefly overviewed the modeling steps of DACM Framework. The framework offers the simulation capabilities, physics-based reasoning and systematic search for contradiction(s) to the functional models in the early design stages. The models developed by DACM are in the form of a combination of the causal graph and a set of behavioral equations. This paper suggests applying the probabilistic simulation using Bayesian networks as an extension of the DACM Framework. The future work of the current research includes applying the approach to explore the design space in the conceptual design phase to reduce the defects in additive manufacturing.

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5. SMART ASSET MANAGEMENT - PATHWAYS TO DIGITAL SERVICE OFFERING

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ABSTRACT

Digitalization disrupts current business models and business environments. Servitization has also gained significant attention in both academic literature and among practitioners. However, there is still a lot of work to be done with respect to digital services being adequately integrated into clients' business processes and the potential benefits of digitalization to be more effectively exploited. Development of digital asset management service portfolios calls for long-term strategic decision-making and visions combined with capabilities for agile development practices. Due to digitalization, companies are facing new service opportunities, and therefore new competences are needed in analytics and understanding of the customers' business.

INTRODUCTION

Creating a successful service offering for a physical product and implementing the services require extensive information exchange across the boundaries of the service provider and client organizations. A change from a transaction- to relationship-based service model calls for new capabilities from the product manufacturer. This change, however, also offers new possibilities for the utilization of lifetime information in a more effective way. (Ahonen et al. 2008, Ahonen et al. 2017)

Customer demands for more services, the desire to be better protected against economic fluctuations, and the desire to achieve growth are among the drivers that make product manufacturers look for more profitable business opportunities in the field of services. Digitalization opens up new scalable opportunities for both larger companies and SMEs globally. It is widely acknowledged that customer should be put in the centre of a new service development process, however, large amount of companies are still in the process of learning new development practices. (Ojanen et al. 2009)

ENABLERS AND BARRIERS FOR DIGITALIZED ASSET MANAGEMENT

Ahonen et al. (2017) have presented an analysis of the enablers and barriers related to digitalized asset management. Understanding the customer's decision-making, requirements and business environment is in the core of developing asset management services. It is also noted that all the capabilities cannot exist in-house but effective partnering is needed. While adopting novel development practices and e.g. agile methods and fast trials, we state that without a systematic development plan there is a risk of individual trials remaining disconnected from the strategic focus of companies. Creating the roadmap and development plan for digital services is therefore a focal step.

Development of a business model for the services needs to be thought carefully right from the beginning. Renewal of the value proposal is a necessity for the company when developing digital services. The drivers for the renewal of business models are stemming from the increased automation level, applications of digital twins, analytics and optimization. The change from transaction-based businesses towards value partnering requires common view on earning and value sharing models. One should thus pay attention to how the key performance indicators are defined for the services.

DEVELOPMENT OF DIGITALIZED ASSET MANAGEMENT SERVICES

Many of the service business frameworks have been understood from the perspective of the transformation from product-based business into service business. However, it has been noticed that companies need to define their role largely based on the existing and developing capabilities, either internally or in the network, and requirements of the business environment and therefore the change from a product provider towards a value partner may not be profitable for all the companies. Furthermore, the role in the value network is dependent on the business environment and capabilities. As stated by Davies (2004), the future (changing) strategic positioning of a company may be an integrator role and the transition may be either downstream or upstream. The key challenge is related to how a company can manage the capabilities required by the larger role. Due to these changes, companies are no longer able to cover all the competences internally and the companies' value chains have been changing towards value networks which support companies in the transformation.

Ahonen et al. (2018a) have presented a framework for the development of digital asset management service business which includes the following phases:

- Identify bottlenecks of the production systems in terms of, e.g. availability, reliability, maintainability, maintenance support performance, quality and resource efficiency.
- Identify opportunities related to how assets are managed to achieve new value, gain knowledge of the desired changes or increase the automation level of the processes.
- Map digital technologies and applications to identify opportunities. Based on the requirements derived from the previous phases, define high-level use cases.

Many companies have started the data-based service business development by starting to gather equipment level data and making visualizations of the data. The first projects typically aim at a proof-of-concept where the technological readiness is demonstrated. Since it is understood that data should be gathered to support the known decision-making situations, it is suggested that a structured and systematic need-based approach is used for creating relevant information content for the service. This requires a solid understanding of the customers' business environment, needs and decision-making processes.

It is acknowledged that one cannot solely rely on the day-to-day customer needs which may be biased and focused on situational bottlenecks etc. but to focus on the variety of new opportunities derived from current bottlenecks, new asset management opportunities and the novel value-creation opportunities related to new technologies. Various methods may be used for the idenfication of customer needs and understanding customer value. These include structured interviews, roadmaps for digitalization, value mapping, tools for customer task identification and business modelling, reliability and criticality analysis, lifecycle cost and profit models, analysis of history data and benchmarking in identifying targets for improvement.

The development of the business models for digitalized asset management services should include considerations for the whole lifecycle of the assets and also the design of the product. Therefore one needs to consider the development as an iterative process where physical assets, ICT and business models are created simultaneously. Collaboration between the disciplines in the company is therefore needed. The development of analytics-based services calls for a systematic approach and clear statements of the objectives. While analytics skills and tools have developed, one needs to integrate the domain knowledge in the development well and define clearly expectations towards the analytics service. However, one should not be locked in to the objectives but be open for changes during the development. When experiences are gathered on how customer value is truly created, one is able to iterate.

We categorize the smart solutions and related service opportunities as shown in Figure 1.

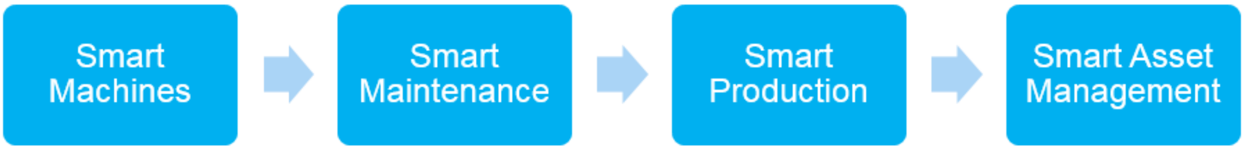

Figure 1. Levels of intelligence.

The levels presented in Figure 1 are defined as follows:

- Smart machine: Smart machine level consists of sensor technologies and analytics capabilities applied at individual component or machine level. The services at this level may vary from the provision of the raw data to optimization of the component or machine reliability.
- Smart Maintenance: Smart maintenance is focused on the upkeep of the assets, at system level instead of machine or component level. The services may vary from data collection to availability performance optimization at production system level.
- Smart Production: Smart production is the level where operations and maintenance activities are integrated and decision-making is supported by providing information from both maintenance and operations disciplines.
- Smart Asset Management: At this level, companies provide new services with Overall Equipment Efficiency and Lifecycle Cost driven focus. Customers are supported in their strategic asset management decisions.

CONCLUSIONS AND FURTHER RESEARCH

Agile methods and experimentation have become the mainstream of service development. They are quick and relatively cost-effective means for testing new data-based asset services. However, as stated earlier, when focusing solely on agile methods, companies are at risk of losing the strategic focus of their service development. The strategy, service portfolio development and business model need to be integrally connected to service development.

Circular economy is a rising trend with significant impact on how the requirements for asset management are defined (Ahonen et al. 2018b). Circular economy related considerations should thus be taken into account at an early stage of the development of assets and related services. Engineering asset management and related services can thus be considered as the means for implementation of circular economy strategies.

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6. ARTIFICIAL INTELLIGENCE AWARENESS – CONSIDERATIONS FOR MACHINE SYSTEM DESIGN

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ABSTRACT

During the last decades, automation systems have replaced human work in many tasks, with the aim to improve productivity and to avoid potentially repetitive and dangerous tasks. While successful in many applications, increasing automation has also raised concerns regarding situation awareness and automation awareness of the users of such systems. In the future, it is expected that an increasing amount of work will be done as co-operation between humans and increasingly autonomous systems that typically apply artificial intelligence (AI). The use of AI, and especially machine learning techniques, brings further awareness-related challenges both for the designers and users of these systems. In this paper, we discuss the concept of artificial intelligence awareness (AIA) from the perspective of machine system design. By following a typical product development workflow, we introduce selected AIA-related challenges to be addressed in different phases of the design process, and discuss the implications of these issues for introducing AI-enabled systems in work environments.

INTRODUCTION

The shift towards increasingly autonomous systems is a global trend in industry. It is expected that in the future, even complex tasks will be handled by systems that apply artificial intelligence (AI), especially machine learning (ML). This is foreseen to increase productivity and safety in many applications, but the changing forms of human-machine interaction will also bring along new challenges and problems. Even with traditional automation systems, it has been noticed that users may have difficulties in understanding what the complex automation is doing, why it is doing that, and what it is going to do next. When applying AI, system developers face further challenges regarding how to provide sufficient user awareness of the AI actions, and how to incorporate these technologies as an integral part of product development activities. These features cannot be developed as a separate process, but instead they need to be considered in all phases of a product development process.

AWARENESS CONCEPTS AND AI

To structure user awareness-related issues in work environments, the concepts of situation awareness (SA) and automation awareness (AA) have been discussed in literature. A widely cited definition of SA is by Endsley (1995), describing it as *'the perception of elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future*'. AA, on the other hand, is not yet an equally established concept. Generally, it can be seen as a part of SA that focuses specifically on automation that comprises of perceiving the current status of the automation, comprehending the status and its meaning to the system behaviour, as well as projecting its future status and meaning.

Artificial intelligence (AI) is also a concept without a single agreed definition. Often, AI is defined as a system capable of understanding its environment and making rational decisions accordingly (e.g. Nilsson, 2009). In this paper, we focus especially on AI technologies with machine learning (ML) characteristics. In industrial machine systems, ML technologies can be used for example in image processing and object recognition tasks. Further uses include various optimization and condition monitoring applications.

ML can further be divided into different development paradigms, such as supervised, unsupervised and reinforcement learning (Jordan & Mitchell, 2015). Each of these paradigms consists of a number of different methods and algorithms that can be used in the actual system implementation. From the system user's point of view, it is not typically possible to know which paradigm (or which algorithm) was used to implement the system.

AI AWARENESS CONSIDERATIONS IN MACHINE SYSTEM DESIGN

When designing complex systems applying AI and involving human-machine collaboration, a set of unsolved and partially unsolved issues exist. To concretize the various dimensions of these issues, the concept of artificial intelligence awareness (AIA) has been proposed as a way to represent a taxonomy for the awareness-related phenomena for AI-enabled systems. AIA in work environments is defined based on the previous definitions of SA and AA as *'the worker's perception of the current decision made by the AI, her comprehension of this decision and her estimate of the decision(s) by AI in the future'.* (Karvonen et. al., 2018)

In the following, we describe some selected AIA issues in the different design phases of a machine system. The design phases listed below follow a systems engineering V-model approach, which is a common method to facilitate a top-down design process of a complex system.

- Concept design: AIA needs to be considered starting right from the early concept design stages. The potential scenarios for human-AI collaboration shall be defined and documented, and taken into account when writing system requirements. The system description needs to be broad enough, to incorporate all potential stakeholders that may interact with the system, as well as the types of these interactions.
- Architecture design: In this phase, data plays a crucial role. The collection, use and handling of potentially large masses of data needs to be carefully planned. The data-related procedures must be documented to be able to provide the user sufficient information regarding the amount and quality of the data used to train the system, and to help select the ML methods best suitable for the application.
- Detailed design, implementation, and integration: In these phases, the main issues include design and implementation for communication and transparency. Careful user interface design is required to provide the user with relevant information of the AI system operation, and for the AI to be able to understand communication intuitive for humans. Transparency (see. e.g. Theodorou et al., 2017) of the system is an issue closely related to communication. In contrast to "black box" ML implementations, proper AIA requires transparency through justification of the decisions made by AI. These can be provided to the user by making the decision-making rationale visible e.g. by using simplifications or visualizations of the AI decision-making process. Well-designed communication and transparency enable appropriate trust (see e.g. Lee & See, 2004) in the AI system, as the user is provided with relevant information regarding the system functioning, capability and limitations.
- System verification and validation (V&V) of AIA related functions is a challenging task, as currently the standardization for AI-enabled machine systems is only starting to develop.

It is likely that extensive simulator-based V&V, involving the actual users of the systems, will be needed. The actual environment of use shall be modelled in V&V, to take into account also the various other tasks the users may need to handle simultaneously when working with the AI system.

- Operation and maintenance: When the system is operational, it is important to ensure that all the users have the sufficient skills to operate the system safely. This is partly an organizational issue, calling for AI-specific training of the workers. Additionally, change management procedures need to be in place to handle maintenance of AI systems, for example to adapt the systems to changing environments of use.

CONCLUSIONS

In this paper, we have introduced selected challenges that system designers are likely to face when developing AI-enabled machine systems for complex work environments. The system designers need to have robust methodology in place to ensure that they provide sufficient information for the users to attain proper awareness of AI systems. AIA needs to be considered in all design phases to address issues such as data collection and handling, appropriate trust, system transparency, and AI-human communication. The concept of AIA can be used to structure awareness-related phenomena and to support the design of systems applying AI. The concept of AIA is also seen as a potential guideline for future research, as several unsolved awareness-related issues still need to be addressed to enable safe co-operation between humans and AI in future work environments.

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7. USER ACCEPTANCE OF AUGMENTED AND VIRTUAL REALITY TECHNOLOGIES IN INDUSTRY

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ABSTRACT

The use of augmented and virtual reality (AR/VR) technologies is increasing in industry. These novel technologies have potential to support many work tasks but to utilise AR/VR solutions, the users should be willing to adopt them. Therefore, it is important to study what influences user acceptance of AR/VR technologies. This paper summarises findings from VTT's AR/VR studies. Main finding is that the users' attitudes towards AR/VR technologies are generally positive. However, they still see challenges in taking the technologies' into use in industry, especially practical problems related to ergonomics, safety and integration to daily tasks. Most of the studies have been short-term and they have been made mainly in laboratory settings. To get a thorough understanding of user acceptance, AR/VR technologies should be studied long-term in actual industrial use.

INTRODUCTION

Industry is undergoing a digital transition, referred as Industry 4.0 that will change the human-machine interaction. In the future, tasks will be performed in cooperation between knowledge workers and smart manufacturing technologies. The integration of virtual and physical worlds is an essential element of Industry 4.0, and this integration is facilitated with AR/VR technologies.

In recent years, the use of VR technologies has increased in product development processes due to the improved availability and lowered prices of VR technologies [1]. VR technologies are being actively used in industry to support decision making and to enable innovations [1]. A collaborative virtual assembly environment is a useful tool for supporting complex product design where each designer can bring their special advantages and communicate with each other. The utility of VR technologies comes up, especially in allowing communication for those who are not familiar with 3D-CAD tools.

The main application areas of AR technologies are in design, maintenance and assembly [2]. AR technologies have been used often for providing instructions and guidance. Hardware devices employed in AR applications can be such as head-mounted displays (HMDs), handheld displays and projection displays. Studies show that AR technologies are feasible in providing instructions since they are often faster to use, errors occur less frequently, and operators approve the technology. Usability has been frequently studied in developing AR solutions [10] but user acceptance studies are rare.

When introducing new technologies at a workplace, it is important to make sure that users accept the new solutions. If users are adopting the new solutions willingly, the full potential of the solutions can be utilised. User acceptance studies are widely used to support the uptake of new technical solutions at work places [3]. User acceptance studies aim to explain the reasons for people's attitudes towards work systems and tools as well as further adoption of the systems.

Many AR/VR studies are related to certain usability issues, are made in laboratory settings, are short-term and do not consider user acceptance. Our goal is to highlight the importance of considering user acceptance when studying novel AR/VR solutions. The purpose of this paper is to review user acceptance of AR/VR solutions based on five user studies. The paper presents the studies shortly and discusses findings regarding user acceptance.

USER STUDIES

Review of a product in a virtual environment [4]

A VR system was developed to review a maintenance platform attached to a mobile rock crushing machine. The purpose of the maintenance platform is to provide a safe, ergonomic and efficient workspace for maintenance workers. The VR system was used in a design review to let the participants understand the maintenance workers' point of view when performing a maintenance task. The participants assessed issues such as task performance, space, safety and reach. The hardware and software included HMD (Oculus), tracking (Vicon), Unity and Middle VR. Ten participants took part to the study. All of them were male design engineers. The study was conducted in a VR-laboratory.

Using a virtual environment in a design review meeting [4]

A VR system was developed to review a noise encapsulation of a mobile rock crushing machine engine. The purpose of the noise encapsulation is to reduce noise emissions to the environment. Design review participants' purpose was to assess the assembly and general feasibility of the product. The hardware and software were HMD (HTC Vive), HTC Vive controller, Leap Motion hand-tracking sensor, Unity and the projector. Eleven participants took part to the study. Ten participants were from the rock crushing machine company and represented roles such as design engineers, design managers, project leaders, development managers, mechanical engineer and technicians. The design review was conducted in a VR-laboratory.

Tablet AR system for guidance in maintenance: [5]

An AR system was developed to support performing a maintenance operation for an elevator hydraulic control unit. The AR system gave guidance by visualising maintenance steps by using 3D models of the control unit and written descriptions of each step. The information was superimposed to the real view of the maintenance technician. The system consisted of the elevator hydraulic control unit and AR guidance software running on a tablet device. Seven male participants took part to the study. The participants were working in an industrial company and they had different roles related to maintenance and training. The study was conducted in an office meeting room.

Smartphone AR system for maintenance: [6]

An AR system was developed to support maintenance workers. The purpose was to illustrate the status information of an electrical system (e.g., condition, fault codes). The system also provided contextual social media features for sharing notes and pictures connected to physical objects with other service personnel. An Android smart phone was used as the platform device. The AR system utilized both marker based and planar image based tracking approaches (VTT's ALVAR SDK). A workshop and a field study were arranged for data collection. Eight male participants from the crane company took part to the workshop: two maintenance technicians, a trainer, a team leader and four managers (product, sales, maintenance and department). The workshop was held in a laboratory setting and the field study on factory floor.

Head-mounted display based AR concept for factory floor workers: [7]

An AR concept was created to show how to visualise information via AR glasses. The purpose of this concept was to provide context related information at the workplace, e.g., to point towards the location of an alarm. The system included HMD (Microsoft HoloLens) and a factory layout model. Two workshops were conducted to discuss the concept. The first workshop was held with a machinery manufacturer in Finland. Eight male participants took part to the workshop. The second workshop was held in a metrology lab of a components manufacturer in Germany. Eight participants (six male and two female) took part to the German workshop. Both workshops were held in an office meeting room.

DISCUSSION

Based on our case studies the AR/VR solutions were well accepted. The participants agreed that the AR/VR solutions are generally easy to use. They thought that AR solutions could make industrial work more interesting and enjoyable. The participants agreed that the use of AR solution could improve the quality of work for example by guiding to follow correct maintenance procedures and making the guidance easily available during the job. AR/VR solutions have potential in improving knowledge sharing, which also can influence work performance and quality of work. The quality of work could improve also when using VR in design. VR gives a realistic experience of the context (real size model and real task). With VR, the designers can step into the users' shoes and get a first-hand experience of the use. This is not always the case when using 3D-CAD or physical prototypes. Easy to use VR models can also be used with actual end users to get early feedback to the design.

Regardless of the positive feedback, there are still challenges in utilising AR/VR technology in industry. Those challenges may hinder user acceptance. Some AR systems can be cumbersome to use. For example, solutions that use HMDs may cause musculoskeletal disorders in long-term use. Users are worried that HMDs may take their attention away from important issues in their work environment. The participants frequently doubted whether commercially available AR-systems would tolerate harsh industrial conditions. For example, if an AR solution is used with tablet PC, it might be difficult to put it aside in harsh maintenance locations such as on the top of a crane or in a narrow engine room. If the use of novel tools is not planned properly, the user acceptance may decrease. It is important to plan together with the user how to integrate AR/VR solutions to the work tasks, and redesign the work tasks to get the full benefit of the new tools. If the new tools do not support smooth work practices, the users may reject the solutions, or they may adopt harmful working postures. The information provided by AR/VR solutions should be reliable to avoid safety risks. Examples of such risks are e.g. human-machine interaction designed in a virtual environment by using wrong size of CAD drawings or an AR solution providing wrong assembly orders. The optimisation of effort and time in content creation should be acknowledged. Organisational issues such as integration of AR/VR systems use to company processes, required facilities and user support may affect user acceptance.

These results have been gained in short-term studies performed mainly in laboratory and office settings. Therefore, the studies can only give initial impressions regarding user acceptance. Especially, with AR solutions, this is a global issue because most current studies are conducted in laboratory settings and do not involve pilot testing [8]. To have a thorough understanding of AR/VR systems' user acceptance, long-term studies should be performed in actual industrial contexts.

CONCLUSIONS

AR/VR technologies are essential part of Industry 4.0. They have a lot potential in integrating physical and virtual worlds, thus supporting future industrial knowledge workers. However, the potential can only be utilised if the users accept the new solutions to their daily work. The purpose of this study was to give an overview of user acceptance of AR/VR solutions in industrial context. Five use cases were presented shortly in this paper, and their results regarding user acceptance were discussed. Based on the use cases, it can be said that in general AR/VR systems are well accepted. However, there are still some concerns especially regarding practical issues such as ergonomics, safety and integration to daily tasks. For this reason, it is important to adopt human-centred design principles when designing AR/VR systems, and to study the solutions in actual work context. Findings from our studies can be utilised when designing AR/VR systems for industrial use.

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8. QUANTIFICATION OF UNPREDICTABILITY IN MANUFACTURING PERFORMANCE INDICATOR MEASUREMENT

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ABSTRACT

Performance Indicators (PIs) are widely used to measure performance of manufacturing systems. A lot of research is undergoing to identify proper performance indicators from factory floor to top-level business decision making. However, little understanding is there on the effects of unpredictability in the measurement of these PIs in complex manufacturing systems. This article presents a technique to quantify the unpredictability in manufacturing performance indicator timeseries with Kolmogorov complexity score and discrete event simulation model. The approach is examined with the superconducting magnet manufacturing facility at CERN.

INTRODUCTION

Complexity modelling in manufacturing is a well-researched topic. Unpredictability, a typical characteristic of a complex manufacturing system, extends lead-time making operations less predictable, costly and difficult to control. A number of analytical techniques have been proposed by researchers to quantify unpredictability in design, manufacturing and supply chain. However, a standard formalized methodology does not exists for quantification of unpredictability in PI timeseries in production. This article proposes a technique for quantification of unpredictability in PI timeseries based on Kolmogorov complexity score and discrete event simulation.

Theoretical complexity modeling and measurement has evolved over the years. In (K.Efthymiou, 2012), the authors propose a taxonomy of five categories for manufacturing complexity analysis. They are Chaos Theory and Non-linear dynamics Theory, Information Theory based on Shannon's Entropy measures, Hybrid Theory, Analogy-based approach of physical domain complexity and theory based on Axiomatic Design. In Chaos Theory, chaotic behavior of a dynamic manufacturing system can be assessed with Lyapunov's exponent. Lyapunov's exponent is used to quantify system sensitivity to initial conditions (K. Efthymiou, 2016). Shannon's information theory or Shannon's entropy was introduced in 1948. Since then many approaches have been developed to model and measure entropy as an indicator of manufacturing system complexity. In (G. Frizelle, 1995), the authors derived a mathematical model for structural complexity from Shannon's Entropy *H(S)*, for *j* machines in *i* states. Structural complexity is classified into dynamic and static complexities. A simplified representation of Frizelle and Woodcook's model is as under:

$$\mathrm{H(S)} = -\sum_{\mathrm{i}=1}^{s} \sum_{j=1}^{M} \mathrm{p_{ij}} \,.\, \log_2 \mathrm{p_{ij}}$$

Where $\mathrm{p_{ij}}$ is the probability of *j* machines being in state *i*; *S* = number of states; *M* = number of machines.

Unpredictability arise in performance indicator (PI) measurement by virtue of the system's stochastic nature. Kolmogorov complexity, an algorithmic complexity measure, was applied in analyzing manufacturing system complexity in (Konstantinos Efthymiou, 2014), (Fan Guoliang,

2017) and (Jiang Kuosheng, 2015). In (Oliver Schwabea, 2016), manufacturing cost variance pattern is identified with Kolmogorov complexity scores. (Konstantinos Efthymiou, 2014) introduces the concept of timeseries binarization. A little consideration will show that PI measurements over certain period forms a timeseries. To analyze complexity in PI timeseries, it is transformed into a sequence *S(i)* having values 0 and 1. That is:

$$S(i) = \begin{cases} 0 & \text{if } I\{i\} < I*, \\ 1 & \text{if } I\{i\} \geq I* \end{cases}$$

Where *I{i}* is the i^{th} value of PI timeseries and *I** is the mean value of the timeseries.

The next section describes a discrete event simulation model for an actual production scenario. The section thereafter proposes a technique of quantification of unpredictability in performance indicators. The following section discusses the result and future work and the final section concludes the article.

DESCRETE EVENT SIMULATION MODEL

A discrete event simulation model is made for 11Tesla dipole coil production at Large Magnet Facility (LMF) in CERN. The time data in simulation model is as per prototype coil data. Figure 1 shows the discrete event simulation model of the winding house.

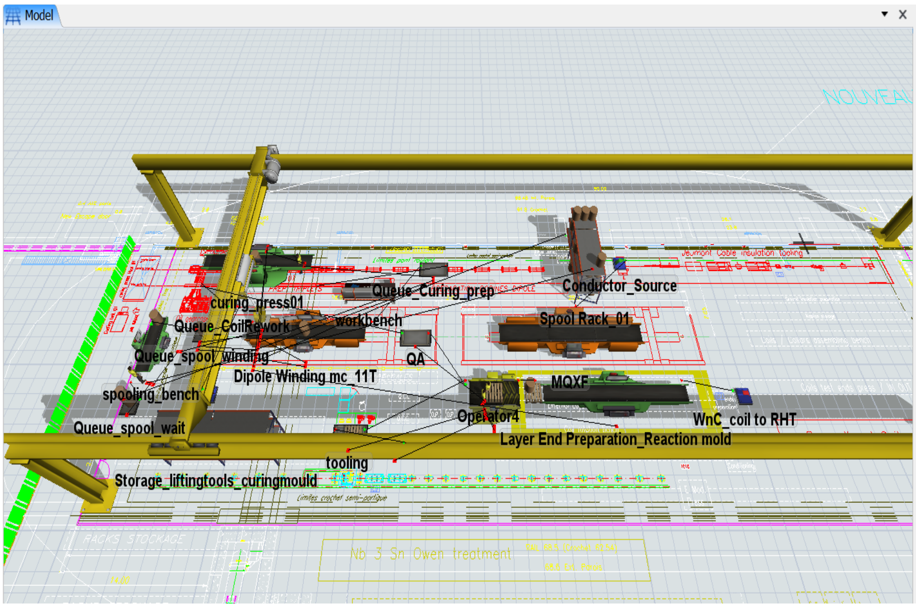

Figure 1. Discrete Event Simulation Model

The production system is assumed to follows Poisson's process with raw material mean inter-arrival rate (λ) = 10.0. Machines are considered deterministic in nature with preset values of set-up time and processing time. Data is recorded form machines, queues and transport devices in the model with statistics collector feature. This simulation data provides important components for building PIs such as Availability, utilization, WIP and throughput for winding and curing process and analyze the relationships between those PIs. The parameters measured from simulation model are:

1. Respooling Waiting Line Time (T_{RWL}) – Average time the spool has to wait for respooling after arrival
2. Respooled coil wait time for winding (T_{RWW}) – Average time the spool has to wait for winding to start
3. Curing Prep Time (T_{CP}) – Average time taken to prepare coil for curing (inner layer and outer layer combined)
4. Curing prep wait time (T_{CPW}) – Average time the coil has to wait for curing preparations to start after winding
5. WnC coils Throughput – (a) Number of coils wound and cured, (b) rework coil
6. WIP curing – Work-In-Progress inventory for curing
7. WnC vs. Rework coil – WnC coils Throughput vs. no of coils needing rework after outer layer curing
8. Winding Machine Utilization – ratio of processing time to idle time of winding machine
9. Curing press utilization - ratio of processing time to idle time of curing press

QUANTIFICATION OF UNPREDICTABILITY IN PI TIMESERIES

To study unpredictability in the performance indicator in totality, set of simulation experiments were conducted. The value of ρ, defined according to (Konstantinos Efthymiou, 2014), is varied from 0.1 to 1 for the inner layer winding process. The PI timeseries is calculated with actual production data and data from simulation model consisting of induced errors in set-up time and processing time. Table 1 shows such unpredictable PI timeseries.

Table 1. Unpredictability in PI timeseries

Time Factors (mins)	data from actual production	unpredictability error									
	Poisson's process with λ = 10.0	ρ(inner)=0.1	ρ(inner)=0.2	ρ(inner)=0.3	ρ(inner)=0.4	ρ(inner)=0.5	ρ(inner)=0.6	ρ(inner)=0.7	ρ(inner)=0.8	ρ(inner)=0.9	ρ(inner)=1
T_{RWL}	10054.42	10438.42	10822.42	11206.42	11590.42	11974.42	12358.42	12742.42	13126.42	13510.42	13894.42
T_{RWW}	5027.21	5219.21	5411.21	5603.21	5795.21	5987.21	6179.21	6371.21	6563.21	6755.21	6947.21
T_{CP}	15008.8	15008.8	15008.8	15008.8	15008.8	15008.8	15008.8	15008.8	15008.8	15008.8	15008.8
Actual production time (APT)	97589.57	97015.57	96439.57	95863.57	95287.57	94711.57	94135.57	93559.57	92983.57	92407.57	91831.57
Planned busy time (PBT)	127680.00	127682.00	127682.00	127682.00	127682.00	127682.00	127682.00	127682.00	127682.00	127682.00	127682.00
KPIs	**data from actual production**	**data with unpredictability ρ**									
Availability	76.43	75.98	75.53	75.08	74.63	74.18	73.73	73.28	72.82	72.37	71.92
WnC Throughput	23	23	22	21	20	20	19	18	18	17	17
Winding Machine Utilization %	93	94	94	95	95	95	95	95	95	96	96
Curing Press Utilization %	21	19	17	16	15	14	14	13	12	11	11

Table 2. Binarization of PI timeseries with sliding window method

Availability	Binary	K (bits)	WnC Throughput	Binary	K (bits)	Winding Machine Utilization %	Binary	K(bits)	Curing Press Utilization %	Binary	K (bits)
76.43			23			93			21		
75.98	0		23	0		94	1		19	0	
75.53	0		22	0		94	0		17	0	
75.08	0	5.3962	21	0	5.3962	95	1	5.5054	16	0	5.3962
74.63	0	5.3962	20	0	5.3962	95	0	5.5054	15	0	5.3962
74.18	0	5.3962	20	0	5.3962	95	0	5.4458	14	0	5.3962
73.73	0	5.3962	19	0	5.3962	95	0	5.3962	14	0	5.3962
73.28	0	5.3962	18	0	5.3962	95	0	5.3962	13	0	5.3962
72.82	0	5.3962	18	0	5.3962	95	0	5.3962	12	0	5.3962
72.37	0	5.3962	17	0	5.3962	96	1	5.4458	11	0	5.3962
71.92	0	5.3962	17	0	5.3962	96	0	5.5054	11	0	5.3962

To quantify the unpredictability in the PI timeseries, Kolmogorov complexity score (K) is used. The sliding window technique and the online complexity calculator, defined in (Oliver Schwabea, 2016), is used for calculation of K. The result of binarization is shown in Table 2.

RESULTS AND DISCUSSION

From Table 2, it is found that Availability and throughput of the process have decreased whereas utilization of the machine has increased when ρ increases from 0.1 to 1. This means with increasing unpredictability in processing time and set-up time, the machine utilization is high even though the Availability of machine (productive time) decrease from 76.43% to 71.92%. Hence, the process gets less productive with increase in unpredictability. This is shown in Figure 2.

This unpredictability is quantified with Kolmogorov complexity score (K). K value is used to identify patterns in the result. Higher the K value, more unpredictable is the process. For Availability and throughput the K value remains constant where as it changes in utilization and becomes as high as 5.5054. This shows that unpredictability not only affects individual PI timeseries but also affects relationships between them.

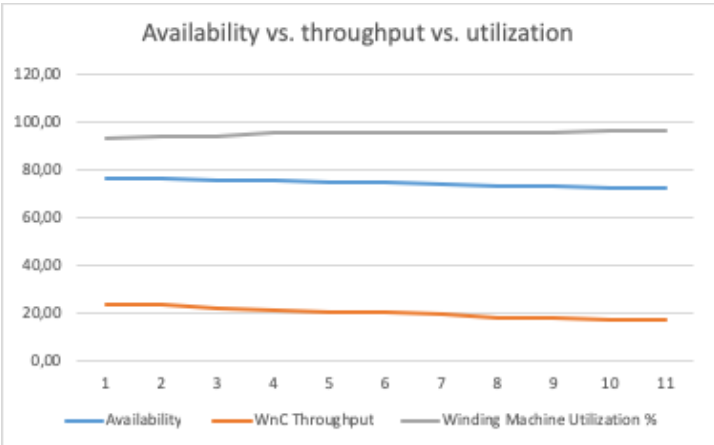

Figure 2. PI relationship in presence of unpredictability

FUTURE WORK

Selection of an optimum number of accurate PIs in cost, quality, productivity and time domains are vital to any manufacturing process. While the approach presented in the article quantifies the uncertainty in PI measurement, a mechanism to model the uncertainty and facilitate decision making of a Gaussian process will require formalized methodology. Currently investigation on manufacturing cost and performance indicator interrelationships is carried out using Bayesian Networks (BN), dimensional analysis conceptual modeling (DACM) framework and modified PageRank algorithm.

CONCLUSION

Discrete event simulation model and Kolmogorov complexity score is used in this article to quantify unpredictability in PI timeseries. It is found that unpredictability affects the PI measurement and interrelation between them. Mitigation of this unpredictability is highly desirable although, an accurate model of unpredictability in PI timeseries in complex manufacturing systems could be extremely challenging to build. This study was conducted under several assumptions. In the future, a robust framework will be developed for accurate performance indicator selection in manufacturing and unpredictability modelling based on Bayesian Networks, dimensional analysis conceptual modeling and modified PageRank algorithm.

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