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Reliability-based cyber plant

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ABSTRACT: With the onset of Industry 4.0 several technological possibilities are offered in industry such as big data analytics, digital twin and augmented reality. The result is a more digitalised industry where faster and better decisions are possible. In long term this should provide a more reliable production with increased plant capacity and reduced downtime. To succeed with these possibilities a Cyber Physical Systems (CPS) must be established for the company. Currently, an own framework for CPS is under development and is expected to be tailored for Norwegian manufacturing. When building on the principle in Industry 4.0, big data capability with machine learning will be a fundamental model. Nevertheless, Industry 4.0 should also include other models for big data capability such as reliability modelling. The aim in this article is to present the current status of CPS framework and how it could be implemented in manufacturing industries. In particular, the article discusses and demonstrates the balance between machine learning and reliability engineering in big data analytics.

1 INTRODUCTION

The European competitive advantage is under pressure, where customer needs, such as improved delivery accuracy of products, have changed over time (Smart Industry, 2017). It might challenge the future industry in Europe how to implement and digitalize equipment and tools for a safe and reliable environment.

Several initiatives like platforms for Industry 4.0 have been established (Kagermann et al., 2013). Also national strategic initiatives have been established, like "Smart Industry" in Netherland (Smart Industry, 2017) and "Industry, greener, smarter and more innovative" in Norway (Ministry of Trade Industry and Fisheries, 2017) where the focus is adapting systems for data handling and digitalization. Several important elements can be related to Industry 4.0 such as predictive maintenance (McKinsey&Company, 2015). The benefit of predictive maintenance is improved reliability with application of the opportunities from big data and statistics where application of continuous real-time monitoring of assets, with alerts given based on pre-established rules or criticality levels (Pwc, 2017). It remains to investigate more in detail how reliability engineering methods also can be combined with big data analytics in order to improve the reliability of the production plant.

Another important element of Industry 4.0 is cyber-physical systems (CPS) (Kagermann et al., 2013). As an overall understanding, CPS are integrations of computation with physical processes (Lee, 2008). Since manufacturing is one essential application of CPS (Lee, 2008), the notion cyber-physical production systems (CPPS) is often used in manufacturing and production (Monostori, 2014, Lee et al., 2017, Hehenberger et al., 2016, Monostori et al., 2016).

Although the economic impact of applying the CPS in manufacturing is significant, computing and network technologies today may impede the progress towards this application (Lee, 2008). For example, the "best effort" in networking technologies make predictable and reliable real-time performance difficult. Nevertheless, certain efforts have been conducted where structures and architectures of CPS have been constructed, ranging from typical sketches with sensors and actuators (Lee, 2010), towards more generic architectures both as level based CPS (Lee et al., 2015) and CPS architecture with three dimensions (IEC, 2017).

Several challenges have been addressed for CPS, such as physical critical infrastructure that calls for preventive maintenance (Rajkumar et al., 2010). It has also been pointed out as a challenge to have a CPS architectures that are both "globally virtual and locally physical" (Rajkumar et al., 2010). Another challenge is need for standards (Chaâri et al., 2016). Although a pre-standard of CPS has been published (IEC, 2017) the industry has already started to test alternative architectures (Lee et al., 2017) in advent for a standard.

In Norway it is of interest to establish a CPS framework for Norwegian Industry. To create such a framework an ongoing competence project where framework, tools and implementation in demonstrators are in progress (Eleftheriadis and Myklebust, 2017).

The aim of this article is to present the current status of a Norwegian CPS framework and how it could be implemented in manufacturing and process industries.

To achieve this aim, following sub objectives are outlined:

1. Present existing elements for CPS architecture
2. Present existing CPS architecture for Norwegian manufacturing and process industry
3. Evaluate how it can be further developed based on existing CPS theory
4. Propose reliability-based analysis methods and technology for the CPS architecture
5. Discuss how the CPS architecture will be implemented in Norwegian industry.

The remainder of this article is structured as follows: In Section 2 existing elements for CPS architectures are presented. Based on these elements the Norwegian CPS framework is constructed in Section 3. In Section 4 three relevant CPS analysis methods and technologies are proposed and elaborated; life cycle profit (1), Safety perspective (2), and machine learning related to reliability engineering (3). Section 5 elaborates how the CPS framework can be implemented, while concluding remarks are made in Section 6.

2 EXISTING ELEMENTS FOR CPS ARCHITECTURES

To ensure successful application of the breakthrough technologies offered in Industry 4.0 in an organisation, a concrete architecture for CPS must be established. Today, there exist several architectures for CPS. In particular three architectures seem to be of relevance in Industry 4.0.

As a first example of CPS architecture, Lee et al. (2015) has proposed a 5-level CPS architecture denoted as the 5C architecture. This architecture provides a step-by step guideline in rolling out CPS in manufacturing with following levels:

1. *Smart Connection level.* Implementing the necessary instrumentation of machines, "plug & play" sensors, and wireless communication.
2. *Data-to-Information Conversion level.* The data collected from the sensors will be input-data for several models that provide information such as assessment of degradation.
3. *Cyber level.* At this level the digital twin of the plant is established and more advanced analytics is possible with assessment of fleet of machines.
4. *Cognition level.* To support the decision-maker to conduct faster and better decisions, proper presentation of the acquired knowledge is necessary. This level visualises e.g. future factory performance and key performance indicators.
5. *Configuration level.* This level provides feedback from the virtual world back to the physical world based on decisions conducted in level 4. This level also self-optimizes several properties of the plant.

Some successful case studies of the 5C architecture have recently been conducted both for ball screw health monitoring (Lee et al., 2017) and a wire rod machine (Rødseth et al., 2016b).

A second proposed architecture for CPS classifies the digitalization of Industry 4.0 into two types of value chains: Horizontal and vertical value chain (Geissbauer et al., 2014). The horizontal value chain comprises suppliers, the company and its customers, whereas the vertical value chain comprises activities in the company such as sales, manufacturing, service and product development.

A third proposed CPS architecture is "reference architecture model industry 4.0" (RAMI 4.0). Currently, a PAS (publicly available specification) has been developed for RAMI 4.0 (IEC, 2017). This specification does not fulfils the requirements for a standard, but is at least made available to the public. The core in RAMI 4.0 is to ensure cooperation and collaboration between technical assets which has a value for an organisation. RAMI 4.0 comprise a CPS architecture visualised with three dimensions:

1. *Layers*. In total six layers represent the information relevant for the technical asset: Business, functional, information, communication, integration and asset.
2. *Life cycle and value stream.* This dimension represent the life cycle of the technical asset.
3. *Hierarchy.* The hierarchy classifies the enterprise system into following categories: Connected world, enterprise, work centres, station, control device, field device and product.

RAMI 4.0 is developed from a more "Generalized Enterprise Reference Architecture Methodology (GERAM) which later was converted to three standards in late nineties. The GERAM was a extension of Computer Integrated Manufacturing (CIM) models which is an early enterprise or business model (Myklebust, 2002). The integration of GERAM and RAMI 4.0 from (Industrial Internet Consortium, 2016) shows the building block of a enterprise model that has interrelationships between organisational, process and product structures. Members of the organisation are connected to process roles defining their work tasks. Competence are connected to process roles, goals are connected to the processes and products, and resources are connected to processes.

The GERAM later RAMI has a well-structured design and fit well with the generic demand of product, process and organisation. The link to the manufacturing system theory is therefore the last approach to include the product configuration and design process of disciplines like mechanics, cybernetic and material science on the physical side and planning activities, economical aspects and optimization processes on the logical side. Theoretically based on geometrical foundation and the methods within the theory that are related to concepts of connections. The analysis of the manufacturing systems is the prime area for the usage of this theory and is important to bring a science base into manufacturing. However how to succeed in developing, managing and operating such an enterprise model is still maybe the main challenge.

3 CONSTRUCTING A NEW CPS FRAMEWORK

Figure 1 presents the proposed CPS framework tailored for Norwegian manufacturing and process industry. With the motivation of establishing a value chain between vendor and the user (Geissbauer et al., 2014) a horizontal value chain has been outlined. In addition, inspired partly by the 5C architecture (Lee et al., 2015), a vertical value chain is also proposed to ensure that data from sensors will lead to smarter decisions. In total a CPS framework with two dimensions are developed.

The horizontal value chain consist of vendor (A), the production (B), and the customer where

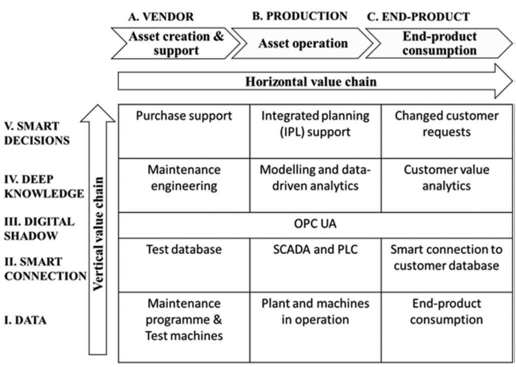

Figure 1. CPS framework.

the end-product is consumed (C). At the vendor the asset is created and the support is provided from the vendor. The vendor can e.g. be a machine builder and supports with providing the maintenance programme. As pointed out by (Smart Industry, 2017) the maintenance could be totally outsourced where all maintenance activities are performed by the vendor and the machine is leased by the user. This will also require a more strategic alliance with the vendor (Batran et al., 2017). The production is where the asset, such as the machine is operated. At this location, an own maintenance management is located to ensure that the required technical condition of the asset is achieved with support from both internal and external maintenance resources. It is a crucial decision for the maintenance management to establish the most appropriate maintenance strategy relevant for the vendor. An important issue for the maintenance management to decide is the correct degree of maintenance outsourcing. The end-product is located at the customer where it is consumed. The customer value will be influenced by production where lack of maintenance can reduce the production assurance and result in late product delivery. Also a defect in production can be undetected and finally discovered by the customer. With application of real-time system, changes in customer requests will be ensured.

The vertical value chain consist of six separate levels of data from assets (I) smart connection to assets (II), a digital shadow of the data (III), deep knowledge application (IV), smart decision application (V). At level I the asset is located that provides value for the organsiation. From the asset all relevant raw data is collected. The asset is not only the asset crated by the vendor such as the machine, but also other technical objects such as data servers, ERP-systems, algorithms and software programs. At this level the raw data is extracted from the physical assets, e.g. data capturing from a temperature sensor in a machine. The next level is smart connection (II) where data is extracted with SCADA and PLC systems and organized in databases such as ERP. To ensure that all databases can exchange data, an own level of OPC UA is necessary. In level IV, it will therefore be possible to apply deep knowledge analytics where databases at production and vendor can provide data-driven analytics in e.g. predictive maintenance.

In level V the deep knowledge analytics will support the decision maker with visualization and dashboards. This level can be considered to be a “digital advisor” for the decision maker. As an example in production, application of key performance indicators in integrated planning can support the planner to improve his future activities.

4 CPS ANALYSIS METHODS AND TECHNOLOGIES

4.1 *Life cycle profit*

Life cycle profit (LCP) is in this article defined as "*accumulated profit of a component or system over it's lifetime*". LCP presents the potential financial losses over the lifetime of a system due to the different time losses measured in overall equipment effectiveness (OEE) (Nakajima, 1989). The profit generated from the system after these losses is then LCP. Table 1 presents a proposed correlation between the time losses in OEE and LCP.

Figure 2 illustrates the LCP model, modified from Rolstadås et al. (1999). The area above the line x-x represents the time losses in accordance with Nakajima (1989). In addition, this area also distinguish between planned and unplanned maintenance. The reason for this distinction is that some of the planned maintenance require a shutdown of the machine and if necessary the production plant. If there are no time losses for the machine, it would be no area above the line x-x and maximum turnover would be achieved.

The area bellow the line x-x represents the costs that occurs during operation of the machine. In this model it is assumed that capital expenditure (CAPEX) is constantly scarred over the operation time. Both the maintenance costs and production costs will be decries in the start and increase at the end of the lifetime. The curve of line B-B will for the *bathtub curve* due to its characteristic shape and is due to the failure rate of the system over its lifetime (Sintef and Oreda, 2009, Rausand and Høyland, 2004). The bathtub can be divided into three specific phases:

- *Burn-in period.* This is an initial phase with high failure rate due to undiscovered defects. This is also known as "infant mortality".
- *Useful life period.* This phase is considered to be the useful period of the system where the failure rate is constant due to the maintenance activities.
- *Wear-out period.* In this phase, the regular maintenance activities can no longer keep the failure rate constant and it will decrease until the disposal of the system.

The LCP should be developed by the vendor with support from production in the CPS framework. With support from historical operations and loads it will be possible to achieve more accurate life cycle profit calculations.

Table 1. Time losses and LCP.

Time loss category	LCP element
Availability	Production Maintenance Resources
Performance	Degraded machine, energy loss.
Quality	Value of product before it is scrapped

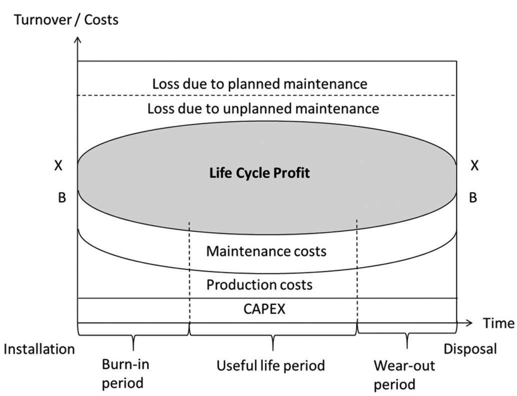

Figure 2. Life cycle profit model, modified from (Rolstadås et al., 1999).

4.2 *Safety perspective*

Regarding the safety perspective, following statements will be important:

- All corrective maintenance is deviation from required function.
- All maintenance activities will have a risk potential.
- Good maintenance is a pillar for effective and safe manufacturing and production.

The safety perspective will be of relevance of following situations:

- Accidents during maintenance
- Wrong type of maintenance
- Lack of maintenance

Table 2 presents a proposal of how these perspectives are relevant for the CPS framework.

4.3 *Machine learning and reliability engineering*

CPS plant position analytics in level IV with deep knowledge. It has been pointed by the European commission that intelligent maintenance systems based on condition prediction mechanisms with computation of remaining useful life (RUL) will increase reliability availability and safety (EFFRA, 2013). Furthermore, more sophisticated techniques for cause-effect and trend analyses are also

Table 2. Safety perspective in the CPS framework.

Safety perspective	Example of position of CPS framework	Example of Application in CPS
Accidents during maintenance	B. Production V. Smart decisions	Application of augmented reality.
Wrong type of maintenance	A. Vendor IV. Deep knowledge	Real-time notification to vendor in maintenance engineering.
Lack of maintenance	B. Production IV. Deep knowledge	Estimation of RUL in real-time with machine learning.

required. The deep analytics has been developed an integrated approach form machine learning and the need for zero defect manufacturing (ZDM). With intelligent sensor system ZDM can be operated for short term, medium term and long term decisions in the EU-project IFaCOM (intelligent fault correction and self-optimizing manufacturing systems) (Rødseth et al., 2016a). It has also been argued that maintenance could be one part of the IFaCOM concept. When advancing towards novel predictive maintenance technologies with reliability-based maintenance approaches, it is pointed out that this should include quality-maintenance methods as well as failure modes, effects, and criticality analysis (FMECA) (European Commision, 2016). Thus it is in this article of interest to investigate how FMECA can be balanced with big data analytics such as machine learning.

The maintenance model called deep digital maintenance (DDM) comprise an artificial intelligence module that tested remaining useful life (RUL) prediction based on dataset of degradation simulation run-to-failure data of jet engines (Rødseth et al., 2017). The output of the prediction model is the probability that RUL is more than 10 cycles in a specific point in time, denoted as $P_r(RUL > 10)$. One cycle is a magnitude for time, e.g. one week.

The prediction model should also include some error estimate to indicate the accuracy. Predictive maintenance should improve the maintenance planning capability in the organization where the plant capacity is increased as well as improved utilization of maintenance resources. The latter can be controlled by capacity overview (Liebstückel, 2014). Due to the operational conditions of degree of prediction in predictive maintenance and the available capacity of the craft technicians, the maintenance window needed by the maintenance planner will vary. Liebstückel (2014) has exemplified the

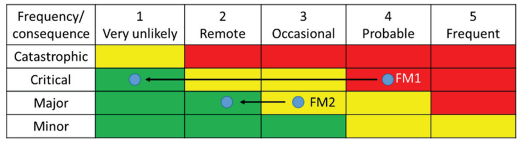

Figure 3. Risk matrix from FMECA, adapted from (Rausand and Høyland, 2004).

maintenance window to be 10 weeks when the planner shall conduct a capacity evaluation.

FMECA evaluates the risk of each failure mode and risk reducing measures. The risk of each failure mode may be positioned in a risk matrix shown in Figure 3 (Rausand and Høyland, 2004). The decision criteria for the risk matrix is as follows:

– *Red area.* The risk is unacceptable and risk reducing measures are required.
– *Yellow area.* Acceptable level of risk. The risk should be as low as reasonable as possible. Further investigations should be considered.
– *Green Area.* Acceptable level of risk. Only consider to keep the risk as low as reasonable as possible.

When the relevant failure modes has been evaluated in FMECA, it is further possible to evaluate to what degree implementation of machine learning in predictive maintenance can reduce the frequency of each failure mode. In the risk matrix, there are two failure modes denoted FM1 and FM2. The failure mode FM1 has non-acceptable risk whereas failure mode FM2 has acceptable but should still be investigate further for risk reducing measures. For both FM1 and FM2 predictive maintenance with machine learning is considered. To reduce the risk for FM1 to the green area, high accuracy in machine learning will be required. For FM2, it is not required the same accuracy in machine learning in predictive maintenance to reduce the risk to the green area.

Following criteria must be considered when evaluating the reduction of frequency due to implementation of predictive maintenance as risk reducing measure:

– The needed maintenance window and the accuracy of the trained data set.
– The similarity of operational conditions from the trained data and the predicted data.

5 ROLLING OUT THE CPS FRAMEWORK IN ORGANISATIONS

In a Norwegian perspective implementation of a CPS framework has to be followed up by guidelines and tools for fulfilling the expected impact. The Norwegian industry is probably one of the most organized labour markets in Europe and consist generally of small and medium size businesses. Where the labour policy for decades has been based on a tripartite cooperation between the government, trade unions and enterprise federations. The result is a flat structure where the involvement of skilled and self-dependent workers has been essential for competing in a global market.

The expectation of digitalizing Norwegian industry is therefore improved performance and a higher productivity. However, thru different maturity mappings, literature and surveys we can see the complexity in CPS and Industry 4.0 is broad. There is an image of a leadership which request for change, but do not find the right tools on one side. On the other hand, impatient workers with high digital competence and a mix match of equipment not prepared for digitalization. (Eleftheriadis and Myklebust, 2017)

A development of regulated safety and quality cultures is one of the benefit from such an organised labour where structure for reliable quality systems, preventive maintenance and management methods are implemented and where the improvement is a part of the organised culture.

6 CONCLUDING REMARKS

The aim of this article is to present the current status of CPS framework and how it can be implemented in Norwegian industry. With sound concepts of CPS theory a framework was proposed to be implemented for Norwegian industry which is both vertical and horizontal integrated. Also the analysis methods LCP and FMECA and different technological application for the safety perspective was recommended for the CPS framework.

The benefit of the CPS framework is that it can integrate all relevant data at sensor level up to decisions at plant level and at the same time connect the horizontal value chain including the machine builder, industrial user of the machine and the customer that consumes the end-product. As an impact for the industry it is expected that the value creation of this framework will be measured in terms of improved asset utilization with improved availability as well as improved product quality with reduced scrappage.

CPS plant will require parallel work with both vertical and horizontal integration of the CPS framework. Further work for the vertical integration will require specification of data capturing including establishment of a detailed specification of sensors that are to be applied in the project. For the horizontal integration, identification of interfaces in the horizontal value chain should be identified and mapping the value across companies.

Further work of the safety perspective would be to build a list of recommended application in CPS framework based on Table 2 and evaluate the reduction of risk. For the LCP, the horizontal value chain should be mapped when the vendor develops the LCP with support from production. The further development of FMECA would require more cooperation between the reliability engineering and machine learning. In detail, this would require simulation where the accuracy of the trained algorithms in machine learning calculates the failure rates as an input for the risk matrix.

For the implementation of the CPS framework, further work would require a detailed road map for Norwegian industry based on findings in demonstration of the CPS framework as well as involvement with several Norwegian companies within manufacturing and process industry.

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