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Preface

This volume contains the papers presented at AP/AD 2023: Automaatiopäivät - Automation Days 2023 held on March 28-29, 2023 in Helsinki.

There were 45 submissions. Each submission was reviewed by at least 2, and on the average 2.1, program committee members. Authors of accepted talks were given the opprotunity to submit a full paper either to a collaborating journal or to the full paper proceedings of the conference. This volume is the full paper proceedings of the conference. There is a separate volume for the extended abstracts of the accepted talks.

May 17, 2023 Seppo Sierla
Helsinki David Hästbacka

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Eetu Heikkilä*, Timo Malm, Risto Tiusanen, Janne Sarsama and Pertti Peussa

Safety and dependability implications of electrification in mobile machinery

Abstract: Electric and hybrid technologies are being developed in the non-road mobile machinery (NRMM) sector to improve efficiency of operations and to reduce emissions. NRMM are used in many different domains and applications. Thus, the business cases and technical solutions for electrification can be very different depending on the application area. In addition to their benefits, electric systems introduce also new types of safety and dependability related uncertainties and risks that need to be controlled. In this paper, we present findings of semi-structured interviews and a literature study focusing on electrification in the non-road mobile machinery sector. As a result, we provide an overview of the different electrification strategies and a structuring of safety and dependability implications of these strategies.

Keywords: mobile machinery, electrification, safety, dependability

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1 Introduction

For decades, internal combustion engines (ICE) have been the predominant means of powering non-road mobile machinery (NRMM). Currently, the quick advances in electrification (i.e., using electricity as the primary energy source) and related technologies bring many opportunities for the NRMM sector. Major driving forces are improvements in energy efficiency and reduction of greenhouse gas emissions. In addition, improvements in performance of the machines are expected. In heavy machinery, especially important factors are the high torque and tractive force enabled by an electric powertrain [1]. These are necessary in applications like carrying heavy loads and working in areas with uneven surfaces. Additionally, the increasing level of automation is a major driving force for electrification [2]. Some examples of currently available electric NRMM are depicted in Figure 1. However, electrification is a target in virtually all domains where NRMM are applied. NRMM are typically highly specialized and the approaches for electrification vary between the different applications. Depending on the electrification strategy, electrification introduces different types of uncertainties and risks related to both dependability and safety of NRMM systems.

Figure 1. Examples of NRMM electrification: Ponsse hybrid forwarder [3], Kalmar battery-electric forklift truck [4], and Sandvik cable-electric loader [5].

As with development of any new technology, the related challenges and risks need to be identified and assessed over the entire lifecycle of the system. In this paper, we focus on the electrification of the drivetrain, i.e., propulsion of the machine. In mobile machines, there are usually also actuators that are used for work tasks like load handling and manipulation. While the actuators were not in the focus of this study, it is noteworthy that also the actuators need to be considered when developing electrified machines. In many machine types, hydraulics is currently used to create the forces required for example in lifting of objects. Especially linear hydraulic systems are challenging to replace with completely electric actuators. This has led to development of various hybrid hydraulic-electric (HHEA) architectures (see e.g. [6]). Regardless of their implementation, the actuators may have effects on the overall dependability of the machine.

The effects of electrification have been studied especially in the automotive industry, but there is only limited research in the machinery sector. For NRMM, various scenarios and strategies for electrification have been proposed [7]. Even more limited research is available on the effects of different electrification strategies on machine safety and dependability performance. In this paper, we focus on the new safety and dependability implications (both opportunities and challenges) of the drivetrain electrification. As a result, we provide an overview of the different electrification strategies and examples of potential use cases for these approaches in the NRMM sector. Based on this, we provide a structuring of safety and dependability related opportunities and risks related to the main electrification approaches.

2 Methods

The research presented in this paper is based on a combination of a literature study on electrification in NRMM, literature-based learnings from safety and dependability implications of electrification in road vehicles, as well as interviews with companies in the NRMM sector.

Semi-structured interviews were performed with four companies involved in mobile machinery manufacturing and electrification of vehicle technologies. For each of the companies, the business cases and approaches for electrification are different as each of the companies operate in different roles (three original equipment manufacturers (OEM), one electrification technology supplier) and in application areas with very different characteristics. In all interviews, the company representatives were from R&D senior and management roles.

The interviews provided insights to the technological questions related to electrification in different contexts. In the interviews, the focus was mainly on the safety and dependability issues and not so much on the economic feasibility of the different electrification strategies. However, the basis for the selection of electrification strategies in companies are based on techno-economic considerations.

In addition to the interviews, a literature study was performed focusing mainly on NRMM drivetrain electrification and safety and dependability of electric road vehicles. The literature study findings were used to identify the different strategies for electrification, bottlenecks for dependability and safety, and to complement the company interviews.

3 Electrification strategies for mobile machines

Currently, a large majority of NRMM are powered by ICEs. Especially battery-electric machines are still rare, while cable electric machines are used in some environments where it is feasible to build the required infrastructure for such use. However, operators and equipment manufacturers are investing increasingly in development of electric battery electric and hybrid machines. In research literature, electrification of NRMM has been studied both from technical and economic viewpoints, focusing on the feasibility of different technical configurations.

According to Forsgren, et al. [8], the total cost of ownership of NRMM can be reduced by electrification if the application area is suitable (e.g., the usage patterns are predictable enough to plan operations), but some barriers also remain. Downtime from charging and unreliable power supply at remote worksites are mentioned as potential bottlenecks for wider electrification.

Ratzinger, et al. [9] have studied three different drivetrains (battery electric, parallel hybrid, and series hybrid) of wheel-driven construction machines from the perspective of reduction of CO_2 emissions. In each drivetrain configuration, the presence of a battery is of key importance as it allows recuperation of energy when decelerating. The study concludes that all the drivetrain types can reduce the emissions when compared to similar diesel-powered machines, with series hybrid being the most promising. Quan, et al. [10] present an overview of powertrain technologies for earth-moving machinery. The study focuses mostly on electrification of the actuators using power electronics or a hydraulic-electric hybrid powertrain.

Lewis, et al. [11] have studied feasibility of electrification in the context of large mobile cranes. In this study, energy storage systems were identified as the major technical bottleneck for electrifying such systems: power requirements lead to the need of very large batteries. In addition to battery electric and hybrid solutions, also hydrogen fuel cell based systems have been proposed as an alternative. Also in these cases, the energy storage becomes a challenge [12].

The previous research on electrification strategies suggests that the feasibility of the electrification and the applicable strategy for it are highly dependent on the intended application of the machine. In all the cases, however, the energy demands and reaching a sufficient energy storage capacity are key issues.

4 Safety and dependability implications of electrification

Automotive sector is a forerunner in electrification and since the recent rapid increase in the number of electric vehicles (EVs), more data is becoming available also related to possible safety and dependability issues. In principle, electric motor as a power source is simple and presumably very reliable when compared to ICE, but other technologies within EVs may cause issues. In consumer use, the reliability of electric vehicles is reported to be under the industry average [13], but the issues are not necessarily related to the drivetrain itself. Hybrid vehicles, on the other hand, perform well in such rankings. Thus, the reliability issues are seen to be mostly related to novelty of the EV technology and the new features incorporated in EVs [13]. In mobile machines, the reliability requirements for components are even higher as the machines are applied in demanding uses.

One key aspect relevant to electrification is the reliability of the batteries, as well as the capacity loss of the batteries over time. The driving cycles, the battery type and the rate of charging all influence the battery reliability [14]. On the other hand, applicable experiences gained from the automotive industry can be utilized when electrifying NRMM.

The use of large batteries creates new challenges also related to fire safety. Batteries are subject to impacts that can lead to heating, ignition, and fire development [15]. Especially Li-ion batteries are subject to the thermal runaway phenomenon, that further increases the risks related to fires and makes extinguishing the fires challenging. The fire safety and handling of battery fires need to be considered in the design of the entire work site.

Batteries are currently expensive and therefore it is profitable to plan the charging procedures to optimize the size of the batteries and the number of machines and charging stations. This has also an effect on complexity of the operations, which can furthermore affect risks. The charging related practices affect the Overall Equipment Efficiency (OEE) of the machines. Whereas EVs can be mostly charged when not in use, such as overnight, mobile machines are typically used with much more demanding duty cycles with limited opportunities for charging. Another approach would be battery swapping, so that the machines can be used without long charging breaks. The reliability of the charging infrastructure is an important aspect to be considered. The availability of the charging devices needs to be fitting for the reliability targets set for the NRMM system.

5 Results

Three main strategies for NRMM drivetrain electrification were identified: battery electric, cable electric and hybrid (with various implementations). Formulated based on the literature study and interview findings, Table 1 provides an overview of key safety and dependability related risks and opportunities of electric machines when compared to ICE powered machines. In the table, the example use cases represent only a small section of possible machine types as most of the machines can be electrified in many ways.

In Table 1, battery electric refers to machines in which all the machine functions are powered by on-board batteries. Cable electric means that there are no large batteries on board, and the electricity is provided using a retractable cable or fixed infrastructure. In some cases, the electric power is provided by wire only when the machine is performing certain tasks that require high power, but the machine can move with an electric or diesel powered tramming capability without the wire connection.

Hybrid in this case means that the propulsion is done by electric motors, but there is an ICE for loading the batteries that power the motors, or to directly take part in the propulsion. Hybrid can also be chargeable from grid (plug-in). As discussed in previous sections, there are various ways for the technical implementation of the hybrid system [4], but in terms of dependability and safety, the different variations seem to have similar impacts.

Table 1. NRMM electrification strategies covered in this study and related opportunities and risks when compared to ICE powered machinery.

Electrification strategy	**Example use cases**	**Dependability**		**Safety**	
		Opportunities	Uncertainties and risks	Opportunities	Uncertainties and risks
Battery electric	Port forklift trucks, Loaders, Automated guided vehicles (AGV), Straddle carriers.	Reduced number of components, Reduced vibration, Inspection and/or maintenance work is possible during charging.	Charging times may interfere with the operative goals, Electromagnetic compatibility (EMC) with other systems, Access to electricity and reliability of charging (or battery swapping) infrastructure, Reliability of the batteries in demanding use, Battery capacity loss over time.	No need for refueling infrastructure and no need to store fuels at worksite, No exhaust fumes, Reduced noise, Precision in operation (good traction control).	High fire load in batteries, Hazardous gases in case of fire, Difficulties in extinguishing battery fires (thermal runaway phenomenon), Electrical safety in maintenance work, Machines are inherently less noisy and more difficult for nearby workers to detect.
Cable electric	Mining machines (loaders, drill rigs).	Reduced number of components, Reduced vibration.	Damage to the cables is expensive and difficult to repair, Electromagnetic compatibility (EMC) with other systems, Reliable access to electricity. Automatic cable handling is challenging for autonomous operations.	See above, also: no high capacity batteries needed.	Occupational safety risks when operating with the cable on the ground, Cable may obstruct onboard safety sensors, Automatic cable handling is challenging for autonomous operations.
Hybrid	Forest machines, Straddle carriers.	ICE can be run at optimal RPM range. Possibility to use only the ICE if needed (parallel hybrid).	Higher number of components and increased complexity due to hybrid technology, Electromagnetic compatibility (EMC) with other systems. In case of plug-in hybrid, need infrastructure for both fueling and charging.	No high capacity batteries needed.	Electrical safety in maintenance work.

6 Conclusions

Electrification of NRMM is quickly advancing. With the wide range of application areas of the machines, the strategies towards electrification are equally varied. This leads also to a wide spectrum of new advanced opportunities for NRMMs but it also introduces new emerging dependability and safety risks. In battery electric and hybrid machines the issues are related to the need of large batteries, charging infrastructure, and increasing system complexity. In cable-electric machines, the risks are mainly related to operation without damaging the cable.

To support the successful development and commissioning of electric and hybrid technologies in NRMMs application area specific safety and reliability analyses are needed to fully understand the implications on safety and dependability in different applications. Such analyses need to be conducted at a system level, covering the entire lifecycle of the system, and also considering the surrounding infrastructure and processes. As a future work, safety and dependability analyses should be more deeply incorporated into the techno-economic considerations of NRMM electrification.

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Predicting the electricity consumption of Finland

Abstract: This paper evaluates the performance and computational requirements of seven different machine learning (ML) algorithms to predict the electricity consumption of Finland. The forecasted period is 24 hours into the future using 24 hours of historical data as an input. The tested ML algorithms were linear regression, random forest (RF), gradient decent regression, support vector regression, multilayer perceptron, convolutional neural network (CNN), and WaveNet. A dataset was constructed by combining three data sources containing historical data about the electricity usage, weather, and industry turnover. The CNN model achieved the best results with both RF and WaveNet in the second place with comparable performance to each other.

Keywords: electricity consumption prediction, machine learning, benchmark

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1 Introduction

Knowing the country's next day electricity consumption in advance would be advantageous. To keep the power infrastructure running a balance needs to be kept between the electricity production and consumption. If the electricity consumption is known in advance, the production can be planned ahead of time with optimal resources. Electricity consumption prediction is not a new concept. Prior art can be found, such as [5], where the authors tested different machine learning (ML) algorithms to predict the power consumption of a university campus. In this study we benchmark different ML algorithms to predict the electricity usage of Finland for the next 24 hours.

2 Materials and Methods

2.1 Dataset

The dataset was generated by combining three open access dataset sources. The electricity consumption of Finland was obtained from the open access download portal hosted by the Finnish national grid operator Fingrid [3]. The data is recorded with one hour interval and includes the total electricity consumption in Finland in MW h/h.

This data was enriched with weather data from Helsinki-Vantaa Airport weather station. Weather changes the heating and cooling requirements of buildings; therefore, it is an important variable to convey for the models. The data was obtained from an open access portal hosted by the Finnish Meteorological Institute [4].

The industry accounts 45% of total electricity usage in Finland [12]. The assumption was that the industry uses less electricity during economic depression, thus the industry turnover was used to convey this information for the models. The data was obtained from Statistics Finland open access portal [11].

Finally, the dataset was supplemented with the information about holidays, time of the week, and the time of the year. Time of the week and time of the year were encoded using the cyclical feature sin/cos encoding technique [8]. The encoding aids the models to understand cyclical features such as the time of the week and time of the year. With naive encoding method, where the week times are converted to numbers ranging from 1 to 168 (168 hours in a week), Monday 1 hour past the midnight is encoded to 1, and Sunday 1 hour to midnight is encoded to 167. The numbers are far apart although in the weekly cycle the times are right next to each other. Converting the time of the week to vectors using the sin/cos method solves this problem.

The dataset consists of a set of input/target samples. The objective was to predict the electricity consumption for the next 24 hours, thus the targets were vectors with the length of 24. The length of the input was likewise set to 24 hours, producing input matrices with a size of 24×19 where the final features were:
- Electricity consumption
- Air temperature
- Air temperature for the next day
- Wind speed

– Wind speed for the next day
– Direct solar radiation
– Snow depth
– Snow depth for the next day
– Industry turnover
– Time of the year (sin/cos encoded)
– Time of the year for the next day (sin/cos encoded)
– Time of the week (sin/cos encoded)
– Time of the week for the next day (sin/cos encoded)
– Days until the next holiday
– Days until the next holiday for the next day

For the models that do not support multidimensional input, the input matrix was squashed to a vector with a length of 456. For the CNN model, the input matrix was constructed without separating the next day's features (air temperature, wind speed, snow depth, day of the week, days until the next holiday) to a separate feature. Instead, the input was constructed for 48 hours making the input matrix to be 48×11. The features that did not have known forecasts for the next day (electricity consumption, industry turnover and direct solar radiation) were set to zero for the hours from 25 to 48.

The generated dataset spanned the period from the 1st of January 2013 to the 10th of December 2019. The data from the year of 2019 was reserved for testing and all other data was added to the training dataset. The samples were generated using rolling window method where the first 24 hours were used as the input and the following 24 hours were used as the target. The next sample was generated by shifting the window one hour over and this was repeated until reaching the end of the dataset. The final dataset consisted of $43,800$ and $8,760$ samples in train and test datasets respectively.

2.2 Models

The tested ML models were linear regression (LR), random forest (RF), gradient descent regression (GRR), support vector regression (SVR), multilayer perceptron (MLP), convolutional neural network (CNN), and WaveNet [9]. These are all well known ML models except for the WaveNet that was added to the benchmark because we had previous experience with the model. The neural network models were implemented using TensorFlow deep learning framework [1], and for the other models an existing implementation was used from the scikit-learn ML library [10].

The random forest model was initialized with 100 estimators while all other parameters used the default values. Likewise, all other scikit-learn models were initialized with the default values.

The MLP model was implemented using five fully connected layers with batch normalization [6] and ReLU [2] activation functions. The unit sizes for the layers were: 8, 16, 32, 64, and 24. The batch normalization layer was located immediately after each dense layer before the activation function was applied. Final layer used linear activation (no activation). Moreover, the model included a dropout layer before the first dense layer. The total number of trainable parameters was $8,832$.

The CNN model was implemented by stacking four convolutional blocks. Each of the blocks were constructed from a convolutional layer, batch normalization layer, and ReLU activation layer. The convolutional layers used 5×5 kernel size with stride 2×1. The number of output filters in the convolutional layers in the different blocks were 64, 32, 16, and 8. The total number of trainable parameters was $114,552$.

Finally, the WaveNet model implementation was the same as what was used in our earlier paper [7]. The total number of trainable parameters was $1,039,872$.

2.3 Experiment Setup

The models were trained using the train dataset and the test dataset was used to compute the mean absolute error, median error, and maximum 97th percentile error metrics. Moreover, the training and inference times were measured. The error metrics were used to compare the model performances, and the measured training and inference times were used to compare the computational requirements of the models.

3 Results

Figure 1 illustrates the accuracies of the different algorithms. The CNN model achieves the highest performance with the lowest scores in mean absolute error and maximum 97th percentile error metrics. The CNN model performance is substantially better in the maximum 97th percentile error metric when compared to the other algorithms. The difference is not as large in the mean absolute error metric with the WaveNet and RF algorithms performing nearly as well. Likewise, the median error metric of the CNN model is comparable to the WaveNet and RF performance which outperform the CNN model with only a small margin.

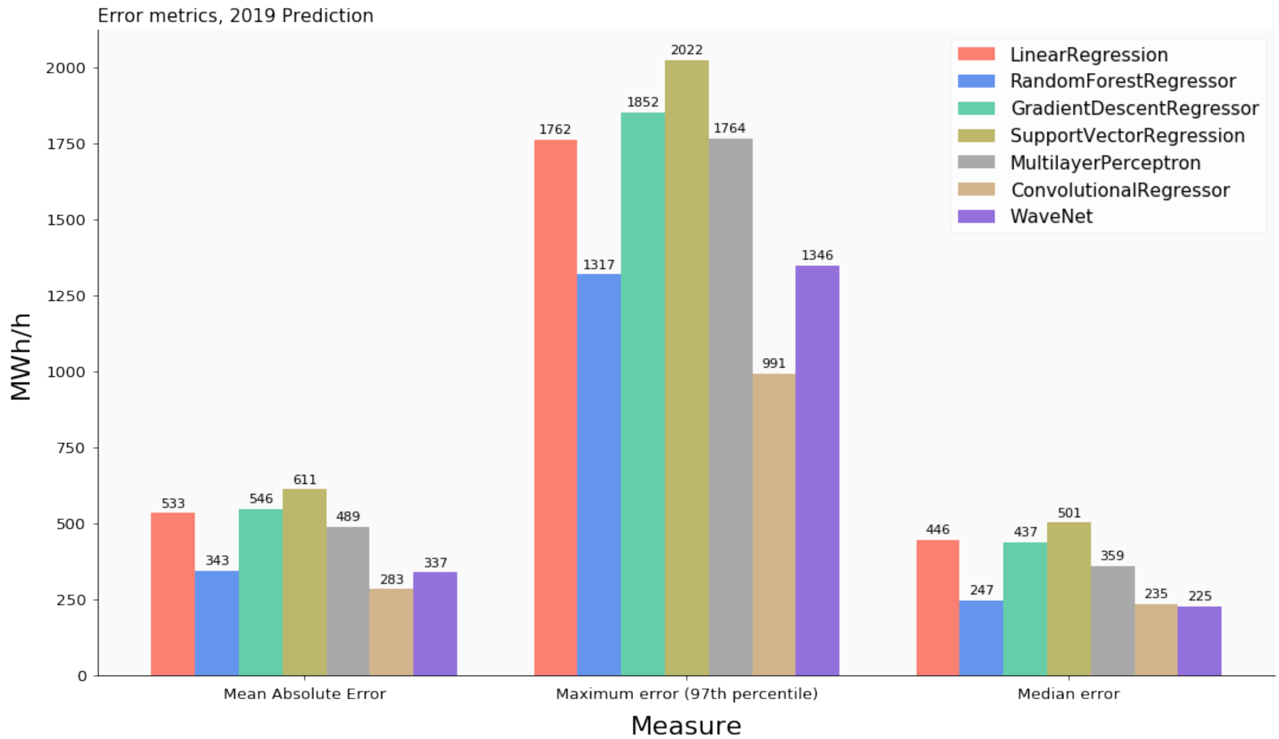


Fig. 1. Accuracy comparison of the different algorithms using three metrics.

The LR, GRR, SVR, and MLP models have clearly worse performance in all three metrics when comparing to the three best performing models. However, even the best performing models have more than 200 MW h/h mean absolute error and median error, which is a large error.

Figure 2 illustrates the predictions for the four best performing models to the test dataset in the year 2019. The plot is smoothed using a 48-hour sliding window that is defined in the Equation 3 where X is the original signal, n is the length of the signal, and $\hat{X}$ is the smoothed signal.

$$X = [x_1, x_2, ..., x_n] \tag{1}$$

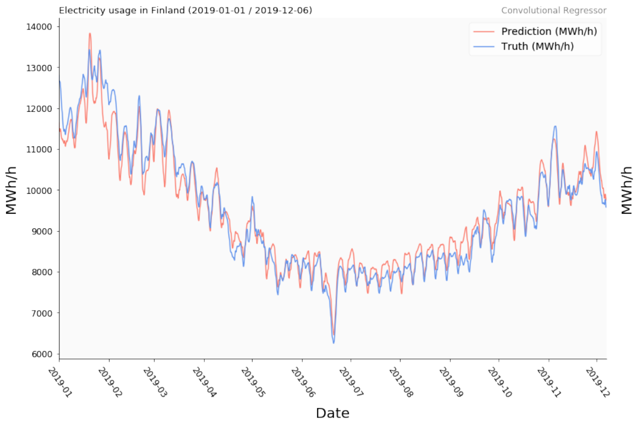
$$\hat{X} = [\hat{x}_1, \hat{x}_2, ..., \hat{x}_n] \tag{2}$$

$$\hat{x}_t = \begin{cases} \frac{x_1 + \ldots + x_{t+25}}{t+25}, & \text{if } t < 24 \\ \frac{x_{t-23} + \ldots + x_{t+25}}{48}, & \text{if } t >= 24 \text{ and } t < n-25 \\ \frac{x_{t-23} + \ldots + x_n}{23+n-t}, & \text{if } t >= n-25 \end{cases} \tag{3}$$

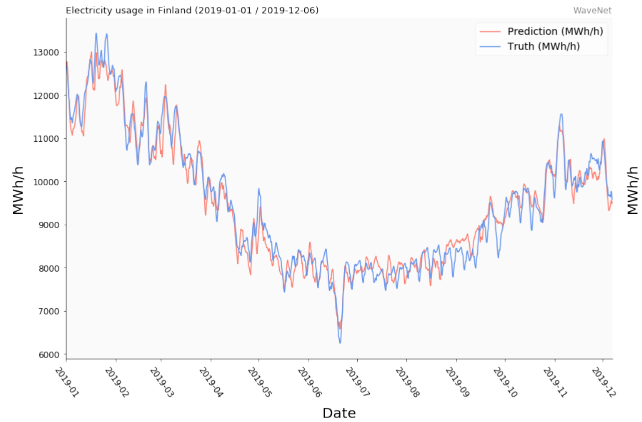
The smoothed signal illustrates better the model accuracy when it is inspected at the span of a full year. Normally the electricity usage includes large changes during the day, thus at the year scale the signal would appear very noisy. However, by smoothing the real and predicted electricity usage signals, the daily accuracies are better highlighted thus creating more readable plot.

Interesting phenomenon to note in the plots are the deviations at the middle of the summer and large variations during the winter. The large dip in the real electricity usage at the center of the plot is positioned around the midsummer festival which is an important holiday in Finland. The large variations in the winter are caused by weather changes where cold temperatures cause raise in heating requirements, thus raising the electricity usage.

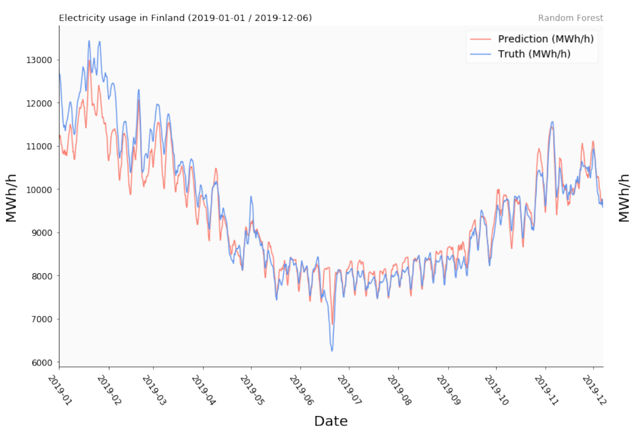
The plots verify the observation that was determined from the collected metrics. The three best performing models in Figures 2a, 2b, and 2c predict the next day electricity usage better when comparing to the fourth best performing model in Figure 2d. The difference is most obvious at the midsummer festival deviation, where the MLP model fails completely to consider the holiday and instead predicts the normal electricity usage pattern. Likewise, the RF model predicts similar usage pattern to continue over the holidays with small dip at the end. However, the two neural network models create excellent predictions for the holiday. The WaveNet model creates the best predictions for the winter variations with good predictions in the beginning of February where all other models struggle. All plotted



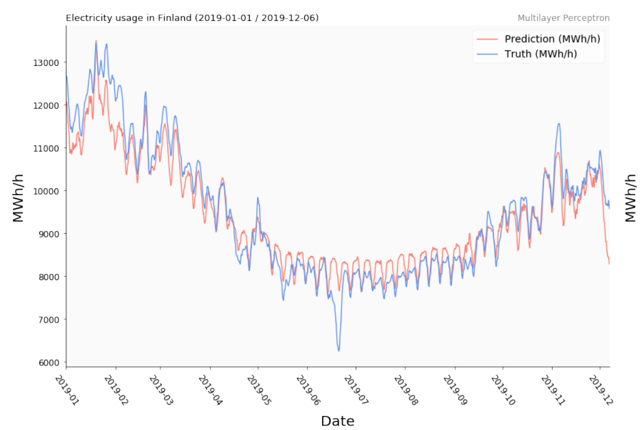
(a) CNN



(b) WaveNet



(c) RF



(d) MLP

Fig. 2. Smoothed model predictions for the four best performing models to the year 2019 test data.

models have a clear tendency to overshoot the predictions during summer and autumn months, however all of them have learned to predict the weekly consumption variation patterns.

In addition of computing the model performance metrics, the training and inference times were also measured from all models. Table 1 lists the times for the different algorithms. Computationally the neural network models are more demanding than the more traditional ML models. Even though the neural networks can efficiently utilize GPUs, the training and inference times are longer when comparing to RF model that runs on CPU and has comparable performance.

Table 1. Computational Requirements.

Model	Train time	Inference time
CNN	5 min (GPU)	0.5 ms (GPU)
WaveNet	30 min (GPU)	85 ms (GPU)
RF	52 sec	0.35 ms
MLP	1 min (GPU)	0.5 ms (GPU)
LR	1 sec	0.04 ms
GRR	10 sec	4 ms
SVR	90 sec	3 ms

4 Conclusions

The CNN model worked the best for predicting the electricity usage for the next day. Comparable performances were measured from the WaveNet and RF models. The RF model is computationally less demanding when comparing to the two other well performing neural network models. Therefore, if the algorithm performance is an important aspect, the RF model is a good option to use. However, the more complex neural network models show better performance in predicting the electricity usage on days with large deviations, such as the midsummer festival.

The goal of this research was to benchmark the ML algorithms. Therefore, the study used a simple dataset that contained only one weather station from the Southern part of Finland. However, Finland is a long country, therefore only one weather station cannot convey the information about weather elsewhere in Finland. This is not a problem in this study since all models were trained on the same dataset, thus the results between the models are comparable and the best performing models can be identified.

However, further study is needed to implement a model that is more accurate and therefore usable in real use-cases where electricity usage prediction is needed. The number of weather stations should be increased to convey more information about the weather in other parts of Finland. The CNN model is the most promising of the tested models and it is likely that it can utilize more input data to make better predictions. The model has a good balance between performance and computational requirements, and the benchmark shows that the model can learn complex information from the input data to make more accurate predictions. Therefore, improving the CNN model would be the recommended choice for further studies in this topic.

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coADDVA - ADDing VAlue by Computing in Manufacturing project which is funded by REACT-EU Instrument as part of the European Union's response to the COVID-19 pandemic.

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Timo Malm*, Daniel Pakkala and Eetu Heikkilä

Autonomous mobile machines in mines and 5G enabled safety principles

Abstract: There is a strong need to have autonomous or semi-autonomous mobile machines in mines. They enable increased productivity and improved safety, as workers do not need to be continuously present in the most dangerous areas of the mine. Several strategies are needed to minimize risks related to collisions. Fences or virtual fences can provide a good safety level, but they are laborious to configure in a continuously changing environment. Tracking of all persons and vehicles, combined with on-board sensors for object detection, could be able to provide dynamic safety without compromising productivity. However, capability in all environmental conditions is not yet adequate. Traffic rules are good additional means to improve safety, but not sufficient for autonomous systems. Almost always, good communication is required between machines, operators and infrastructure. Lost integrity or availability of communication can have impacts on safety and production. 5G introduces new possibilities to build reliable and quick networks.

Keywords: Functional safety, mining operations, autonomous mobile machines

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1 Introduction

This paper focuses on new safety principles enabled by 5G, pointing out risks, mitigation strategies, functional safety principles and communication safety principles. A comprehensive study will be available in VTT Technology publication "Autonomous mobile machines in mines using 5G enabled operational safety principles" [1]. This paper introduces selected ideas of safety functions, which can be applied with autonomous mobile machines in mines. The focus is on cases where 5G communication is applied.

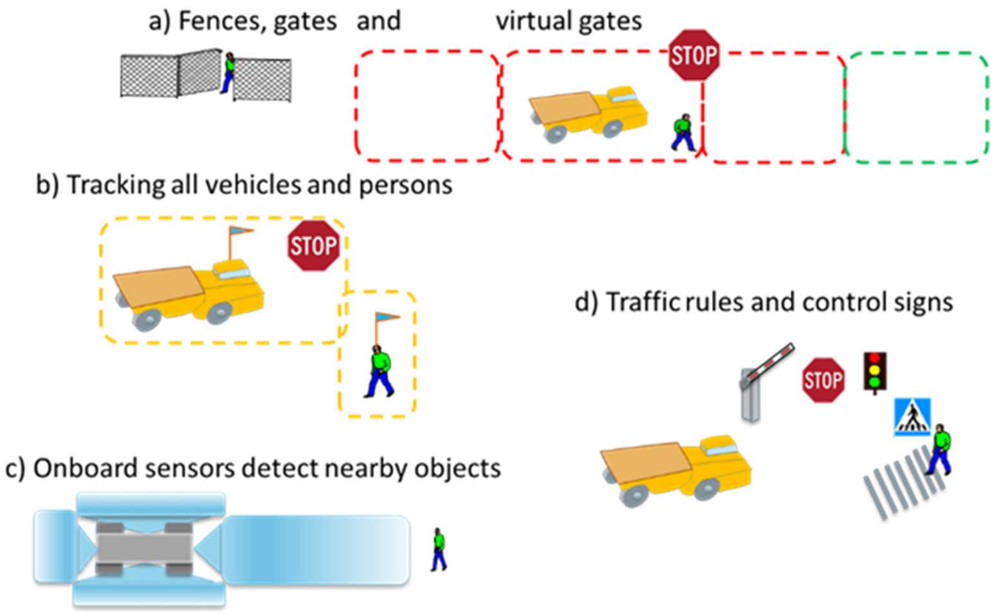

Figure 1 Strategies to mitigate autonomous mobile machines collisions.

The focus of this article is on collision avoidance and related communication. Autonomous mobile machines are typically large, and all collisions cause considerable damages. If a person is involved with the collision the severity is considered fatal in the risk assessment. Also, a collision of two driverless vehicles can have hazardous consequences in mines.

The strategies to mitigate risks are here divided into 4 groups presented in Figure 1: a) fences, gates and virtual gates/fences, b) tracking of persons and vehicles, c) on-board sensors to get an overview of objects in the vicinity, d) traffic rules. To make a safe mobile machinery system in mines often several mitigating strategies are needed. Communication between machines, operators, fleet control and infrastructure, is necessary in all of the strategies. Sensors onboard the mobile machine (case c) at the figure) could operate for a while without communication, but there must be means to stop all machines and for emergency stop, communication is required. [1]

One aspect related to communication is that safety means are concentrated on safety layer, which is above actual communication protocols [2]. In many cases, messages need to be sent via several stations using wireless or wired communication. The logical communication between safety layers of two nodes is considered black channel, which may have different safety capabilities, which can be difficult to evaluate in a dynamic environment.

2 Methods

The research was done in NGMining project, and the ideas of safety strategies have emerged in literature, discussions, presentations and workshops in the project. There have been several case studies in the project related to communication (mainly 5G). The results are gathered more detailed to VTT Technology publication 412: Autonomous mobile machines in mines using 5G enabled operational safety principles [1].

3 Communication and safety in mines

Communication in mines

Wired high-speed communication is usually arranged from surface to specific control rooms, which can provide wired or wireless communication to other parts of the mines. Radio waves cannot go through rock and therefore line-of-sight contact between radio stations is needed or so-called leaky feeders (cable radiates/communicates to its vicinity) are applied.

It is important to choose communication topology according to mine structure and environment, in order to minimize consequences of failures. Common communication ideal topology models in mines are :

- bus topology, which has all nodes connected to a single linear connection,
- ring topology, which has all nodes connected to a ring,
- mesh topology, which has nodes, which are connected to all the other nodes (in the vicinity),
- star topology, which has central hub, where other nodes are connected via dedicated path.

Real topologies are combinations of ideal topology models.

Currently Wi-Fi is very common technology for wireless communication in mines, due to low purchase price and general knowledge. However, in mines reliability and, especially, availability is important property due to very expensive unavailability costs. 5G has some advantages related to reliability. Here are some reliability-related properties of 5G compared to Wi-Fi [1]:

- In 5G the handover between stations is made by comparing stations and choosing station according to signal strength, signal/noise ratio, and by avoiding swapping of station too often (hysteresis). In Wi-Fi, there is no comparison of signals and the communication needs to end before establishing communication via new station/repeater. There can be also a short period of weak signal, before communication ends, which may cause delays.
- The applied frequency of 5G can be chosen so, that no other devices apply the frequency and the disturbances are so minimized. Usually lower frequency travels longer distance, but it does not carry so much information.
- When the 5G network can be established by avoiding disturbances, it may be possible to lower the number of stations, but there is balance between reliable communication and number of stations. Usually, the stations need to be placed at locations, where is long line-of-sight and therefore possibility to lower the number of stations can be small.

Safety of communication

Currently, it is very difficult to make safe mine automation by applying only on-board systems (sensors, warning devices). Of course, there are also other than safety needs for communication. Safety-related needs for communication are for example:

- safety messages, like emergency stop, fire alarm, acknowledgements, failure/malfunction information,
- area access control requests, permissions and commands,
- tunnel blocked/reserved or digital terrain map,
- situational awareness is needed for workers to know, where machines are
- situational awareness for fleet control to know status and where (position, speed and direction) autonomous and manual mobile machines and persons are,
- traffic lights, open/close gate.

According to Machinery Directive: “For cableless control, an automatic stop must be activated when correct control signals are not received, including loss of communication” [4]. Autonomous mobile machines were not yet defined when Machinery Directive was published (2006) and there was no need to mention exceptions. According to new proposal of Machinery regulation: “For wireless control, a failure of the communication or connection or a faulty connection shall not lead to a hazardous situation” [5]. Similarly, standard ISO 17757 Autonomous and semiautonomous machine system safety requires risk assessment and safe state, which may mean also other functions than stopping of the machine [6]. There can be places in mines, where wireless communication is not available. If there is no communication, then for example emergency stop command cannot be delivered and risk assessment is needed to assess has the mobile machine adequate situational awareness to continue the operation and on which conditions. The detection capability of the machine sensors needs to be adequate without blind spots and safety performance of the stopping function (including sensors, logic and actuators) needs to be typically PL d (Performance Level) according to ISO 13849-1. The safe performance of the autonomous mobile machine is difficult to prove if the communication has failed and therefore operation can continue only for a short time (defined by risk assessment). Actually, it can be a matter principle, may the autonomous mobile machine continue operation, if there is no possibility to stop it remotely.

Safe communication structure

Figure 2 shows how communication between two safety layers can be divided into logical connection and black channel. The failures of the black channel are not defined and there can be failures, or the failures can be detected, but the safety layer does not trust the possible protective means. Safety layer builds up its own protective shield, which covers timeliness, authenticity, data integrity and if needed, also security. According to OSI model (Open Systems Interconnection model) communication is operated through standardized layers: physical layer, data link layer, network layer, transport layer, session layer, presentation layer, application layer and above them is safety layer [1].

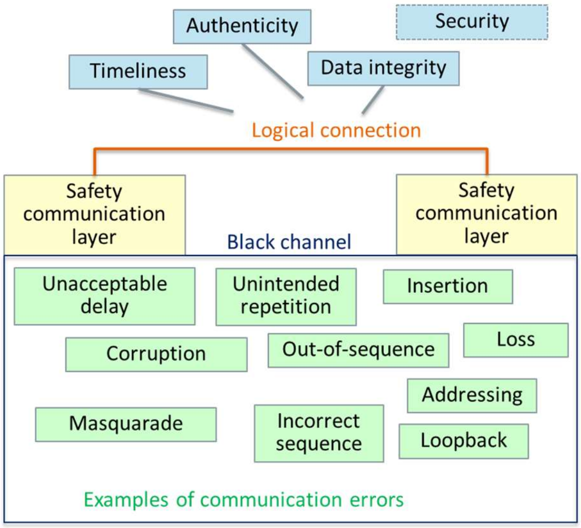

Figure 2. Black channel from a functional safety communication profile perspective [1], [2].

Figure 3 shows an example how message is first built up at the safety communication layer, it is delivered through lower layers and internal communication link to the gateway. Next the message goes through fieldbus and possible other communication media to the target node and its layers finally to the safety layer. Safety layer checks authenticity, integrity and timeliness. Failed messages are discarded. Failed message is often detected before safety layer and the message is asked to be repeated.

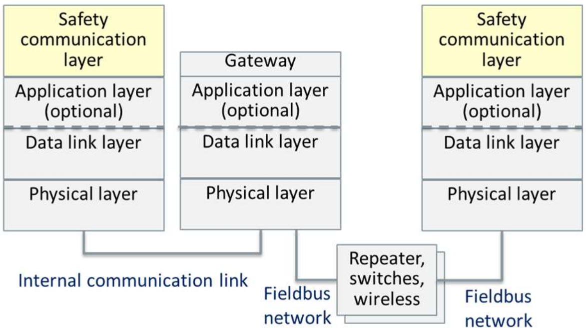

Figure 3. An example of black channel communication [1], [2].

The safety of communication and safety layer relies very much on timeliness, authenticity and data integrity of messages. Actually, the system needs to have adequate means to control defined errors/threats: repetition, deletion, insertion, incorrect sequence, corruption, delay and masquerade (and sometimes addressing, depending on error definitions). [1], [2]

Cybersecurity or security are described in different standards than functional safety issues. Cybersecurity issues can be controlled in several layers and therefore it does not have to be on safety layer. However, properties like integrity and in some cases, availability are common for both cybersecurity and functional safety. In some cases, there can be contradictory objectives for functional safety and cybersecurity. Uncertain communication leads often to stopping of the machine due to safety reasons, but from cybersecurity objective point of view stopping means unavailability, which should be avoided. On the other hand, cyber-attack may lead to countermeasures, which limit access to communication media. However, from functional safety viewpoint, the safety messages may not be limited or otherwise the complete system needs to be stopped.

The machine automation designers select the communication system according to requirements. This means that system needs to fit to the environment, performance is adequate for the application and safety performance level (PL) is according to made PL assignment for each safety function.

4 Results and conclusions

The safety and availability of communication are important factors in mines, especially in future digitalized mining, where physical mining process are increasingly automated and executed by teleoperated or fully autonomous mining machines. In highly digitalized and automated mining operations the availability of communication had key role in ensuring continuity of production at the mining site. Safety issues are often related to integrity of messages and there are requirements for integrity, for example, safety integrity level 2 (SIL) (=PL d). Availability requirements can be related to safety, but typically loss of communication leads to a safe state i.e., stopping. The time to endure communication delays needs to be defined in risk assessment. For example, in bridge cranes the acceptable time delay is typically 500 ms and similar value can be applied in mobile machines too. Although availability issues do not usually cause safety issues, a long-lasting communication loss can cause huge financial losses due to lost production.

The communication systems in mines are changing continuously as new tunnels are built. Therefore, some parts of the communication can be difficult to be defined as white channel according to IEC 61508-2 [7]. Safety measures can be done also in sender and receiver in their safety layer. This means that the communication is made in black channel, which includes 5G. Since 5G is inside the black channel, its properties are not considered in safety assessment of the communication channel. However, reliable communication affects the share of messages that the safety layer accepts and furthermore it has an effect on dependability in general.

A relatively new category of risks in mine communication are related to cybersecurity. The mines are usually deep underground and therefore general cybersecurity threats/attacks are rare. However, it is wise to consider vulnerabilities of communication and control systems to avoid cybersecurity issues.

Strategies and principles to mitigate collision risks need to be chosen. Most of the strategies require safety functions, which are related to control systems and communication. Safety functions are related to functional safety, including safety integrity levels (SIL) and performance levels (PL). Furthermore, control systems are related also to cybersecurity and dependability in general.

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Outi Rask*, Jari Seppälä, Antti Väätänen, Susanna Aromaa ja Antti Tammela

Prosessiautomaation innovaatioalusta

Tiivistelmä: Pirkanmaalle kehitetään prosessiautomaation innovaatioalustaa yhteistyössä Tampereen ammattikorkeakoulun (TAMK), Tampereen yliopiston (TAU) ja VTT:n Tampereen yksikön kanssa. Hankkeessa rakennettava innovaatioalusta rakentuu kolmeen toimipisteeseen ja tarjoaa monipuolisen, nykyaikaisen testausympäristön prosessiautomaation erilaisiin ja eriasteisiin kehitys- ja testaustarpeisiin. Tässä artikkelissa esitellään innovaatioalustan alustavaa konseptia. Kirjoitushetkellä hanke on vielä kesken ja alusta on vielä kehitysvaiheessa.

Avainsanat: innovaatioalusta, automaatio

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1 Johdanto

Tampereen ammattikorkeakoulu (TAMK) on yhdessä Tampereen yliopiston (TAU) ja VTT:n Tampereen toimipisteen kanssa kehittämässä ensimmäistä erityisesti prosessiautomaation parissa toimiville Pirkanmaan alueen pk-yrityksille suunnattua innovaatioalustaa. Jokainen organisaatio rakentaa oman innovaatioalustan omiin tiloihinsa siten, että alustat ovat vuorovaikutuksessa keskenään.

Alustaa kehitetään EAKR-rahoitteisessa Prosessien älykkään digiohjausjärjestelmät -hankkeessa, jota myöhemmin tässä artikkelissa kutsutaan lyhenteellä PRODI. Hanke alkoi helmikuussa 2022 ja päättyy 31.8.2023. (PRODI 2023)

Innovaatioalustaa on määritelty eri lähteissä hieman eritavoin. Aiheesta löytyy sekä tieteellisiä artikkeleita että yleistajuisempia kirjoituksia. Päädyin määrittämään tässä artikkelissa tämän käsitteen jälkimmäisen tyyppisten kahden lähteen avulla.

Business Tampereen artikkelin (Business Tampere 2015) mukaan innovaatioalusta on eräänlainen paikka tai ympäristö, jossa mahdollisimman helposti ja nopeasti päästään kokeilemaan, kehittämään ja testaamaan esimerkiksi erilaisia uusia teknologioita. 6aika -hankkeessa (6aika 2016) taas innovaatioalustaa määritellään toimintaympäristöksi, teknologiaksi, järjestelmäksi, tuotteeksi tai palveluksi, jonka kehittäminen on systemaattisesti avattu ulkopuolisille kehittäjille ja arvonluonnille.

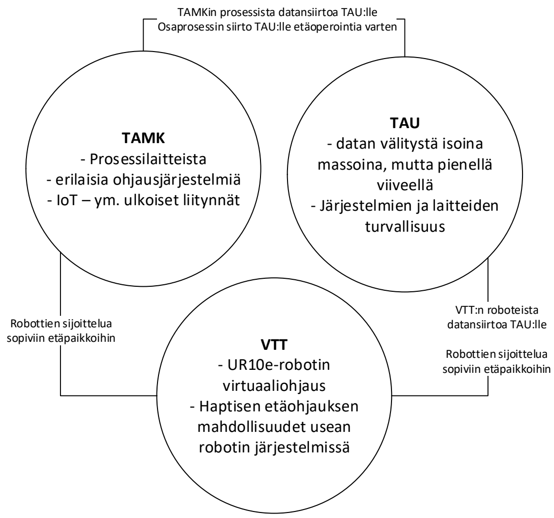
Molemmat näistä kuvauksista vastaavat hyvin sitä, mitä tässä hankkeessa innovaatioalustalla tarkoitetaan. Hankkeessa kehitettävä innovaatioalusta on tarkoitettu prosessiautomaation alueella toimivien pk-yritysten ympäristöksi, jossa he voivat tutkia ja testailla kiinnostavia uusia teknologioita. Monellakaan pienellä tai keskisuurella yrityksellä ei ole resursseja eikä tiloja hankkia testilaitteistoja, joten tästä toivotaan ratkaisua tähän haasteeseen.

2 Innovaatioalustan esittely

Pirkanmaalle rakennettava innovaatioalusta koostuu prosessiautomaatiota hyvin monipuolisesti palvelevista osakokonaisuuksista (kuva 1). TAMKin ympäristöön rakennetaan monipuolinen mittausta, säätöä ja erilaisia ohjaussovelluksia tukeva testialusta. Ympäristöstä on avoimet rajapinnat mm. tiedonsiirtoa varten.

Tampereen yliopiston osuus keskittyy isojen tietomassojen turvalliseen ja nopeaan siirtämiseen. Tässä hyödynnetään TAMKin Kaupin kampuksen ja Tampereen yliopiston Hervannan kampuksen välille rakennettua DS CyberLabs valokuituverkkoa (Rask et. al. 2021) (Dependable Systems 2023).

VTT:n ympäristö puolestaan keskittyy pienikokoisten teollisuusrobottien haptiseen etäohjaukseen (González et.al. 2021). Tällaisia robotteja voidaan prosessiteollisuudessa sijoittaa esimerkiksi paikkoihin, joissa ihmisten on vaarallista tai haastavaa toimia. Hankkeessa keskitytään pääasiassa yhden robotin haptiseen ohjaukseen, mutta tavoite on laajentaa PRODI-hankkeen tulosten perusteella tutkimusta useamman robotin samanaikaiseen ohjaukseen.



Kuva 1. PRODIn innovaatioalustan toiminta-ajatus.

Seuraavissa luvuissa esitellään jokaisen organisaation ympäristöjä hieman tarkemmin.

3 Tampereen ammattikorkeakoulun ympäristö

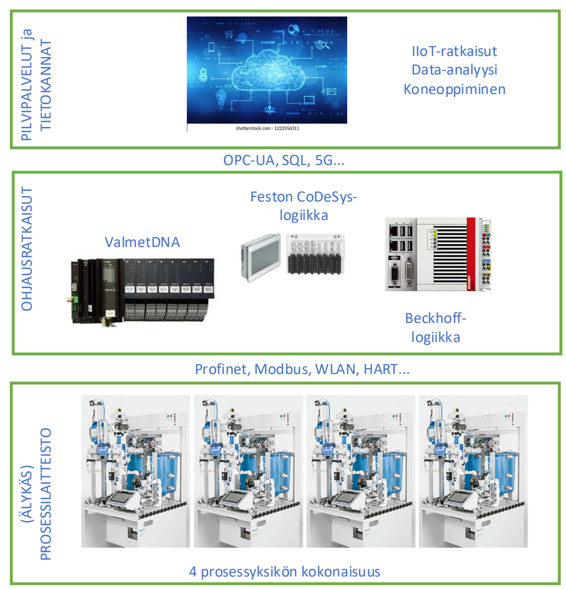
Tampereen ammattikorkeakoulun tiloihin rakennettavan ympäristön keskiössä on Festo Didacticsin valmistama prosessituotantolinjasto, joka koostuu neljästä osaprosessista: suodatus, sekoitus, reaktori ja pullotus. Osat toimivat yksittäin mutta myös yhdessä kokonaisena tuotantolinjana. Jokainen osaprosessin toiminnallisuus keskittyy johonkin prosessien mittauksen ja säädön kannalta keskeiseen suureeseen: virtaukseen, lämpötilaan, paineeseen tai pinnankorkeuteen. Jokaista pystyy tarkkailemaan sekä mittaus- että säätöteknisestä näkökulmasta. TAMKin ympäristön konseptia on esitelty alustavasti kuvassa 2.

Jokaisella osaprosessilla on oma ohjaimensa. Avoimen rajapinnan ansiosta jokaiseen näistä voidaan liittää erilaisia ohjelmoitavia logiikoita eri valmistajilta tai vaikka hajautetun automaatiojärjestelmän prosessiaseman. Hankkeessa on tarkoitus demonstroida ympäristöä liittämällä laitteistoon mm. Siemensin, Beckhoffin ja Feston ohjelmoitavia logiikoita sekä ValmetDNA-järjestelmä (DCS-järjestelmä). Ympäristössä on näin olleen mahdollista demonstroida DCS-järjestelmän muodostusta erillisen SCADA-ohjelmiston ja eri toimittajien ohjelmoitavien logiikoiden muodostamana kokonaisuutena. Samalla päästään tutkimaan mm. erilaisten järjestelmätyyppien välisiä eroja sekä niiden hyötyjä ja haittoja.

Ympäristöön tullaan sijoittamaan myös erilaisia OT-tason (operational technology) tiedonsiirtoa tukevia älykkäitä kenttälaitteita. Näitä ei vielä tätä kirjoittaessa olla valittu kaikkia, mutta luultavasti tullaan toteuttamaan neljä erillistä demoa näihin liittyen: pari uudemmilla teknologioilla, kuten ProfiNet ja IO-link sekä pari perinteisemmällä tekniikalla, kuten HART ja milliamppeeriviestit.

Laitteistoista on myös tarkoitus kerätä dataa, jota analysoidaan muun muassa koneoppimisen menetelmien avulla. TAMKin ympäristöstä kerättävää dataa voidaan käyttää myös Tampereen yliopiston datansiirtojen demoamiseen. Datan keräykseen tullaan käyttämään ainakin OPC UA-spesifikaatiota.

Yksi keskeinen osa TAMKin ympäristöä ovat myös digitaalisten kaksosten rakentamisen periaatteiden selvittäminen sekä demoaminen. Näitä malleja ja niiden toteutusperiaatteita voidaan myöhemmin hyödyntää esimerkiksi etäkäyttöönottojen testailemisissa ja tutkimisessa prosessiautomaation kohteissa.

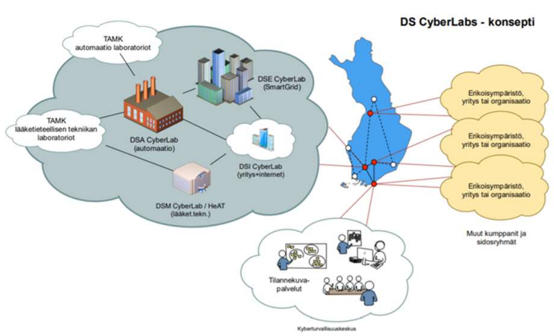


Kuva 2. TAMKin ympäristön periaatekuva.

4 Tampereen yliopiston ympäristö

Tampereen yliopiston ympäristössä isoimmassa roolissa ovat suurien datamäärien siirtäminen tietoturvallisesti ja pienellä viiveellä. Tätä ratkotaan viemällä data GPU (graphics processing unit) kiihdytettyyn laskentaan, jossa hyödynnetään tekoälypohjaisia analyysimenetelmiä. Tässä tullaan laitteistossa hyödyntämään siruun integroituja kiihdyttimiä, jotka ovat kooltaan pienempiä.

Pienet viiveet liittyvät keskeisesti myös järjestelmien turvatoimintaan. Esimerkiksi niiden avulla voidaan parantaa järjestelmien turvallista vikaantumista.



Kuva 3. TAU:n ympäristö rakentuu olemassa olevan Debendable Systems CyberLabs-konseptin päälle. (Rask et.al 2021)

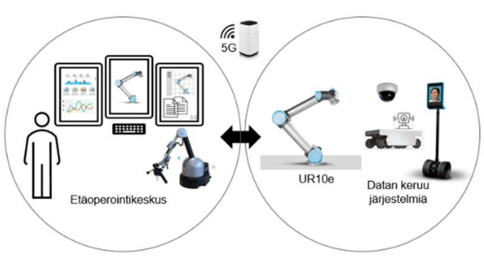
Tietoturva liittyy oleellisena osana TAU:n ympäristöä. Tässä hankkeessa tietoturvaan liittyviä käyttötapauksia on valmisteltu muun muassa aiemmissa hankkeissa, joista keskeisimpiä ja viimeisin on KyLÄ-hanke (KyLÄ 2023). Näitä käyttötapauksia viedään käytäntöön PRODI-hankkeessa.

Tässä paperissa esitettävässä innovaatioalustassa organisaatioiden väliseen kommunikointiin on tarkoitus hyödyntää KyLÄ-hankkeessa TAMKin tiloihin laajennettua CyberLabs-verkkoa (ks kuva 3). VTT tulee liittymään kokonaisuuteen 5G -verkon kautta kuvassa 3 näkyvän erikoisympäristön mukaisesti. Samalla demonstroidaan verkkoon liittymistä TUNI-organisaation ja valokuitupohjaisen DS CyberLabs -verkon ulkopuolisista organisaatioista. Samankaltaista menetelmää hyödynnetään myös yritysten liittyessä omilla järjestelmillään innovaatioalustaan.

Dependable Systems CyberLabs -verkkoa ylläpidetään Tampereen yliopiston ja Tampereen ammattikorkeakoulun toimesta. Ympäristöä kehitetään jatkuvasti eteenpäin entistä paremmaksi ja sitä laajennetaan eri organisaatioihin ympäri Suomea. (Dependable Systems 2023)

5 VTT:n ympäristö

Tässä kappaleessa esitettävä VTT:n ympäristö on



Kuva 4. VTT:n ympäristön periaatekuva.

valmisteilla ja joitain muutoksia voi vielä tulla suunnitelmaan. Tavoitteena on luoda multimodaalinen etäoperointikeskus, jossa operaattorilla on ajantasainen ja tarvittava tieto etäoperointikohteesta. Operaattori voi myös halutessaan käyttää operoinnin ja valvonnan aikana erilaisia välineitä, jotka tukevat monimuotoista vuorovaikutusta.

Ympäristö perustuu UR10e-robotin etäohjaukseen haptisen laitteen (VirtuoseTM 6D TAO) avulla. Haptista laitetta käytettäessä operaattori saa tuntopalautetta robotin liikkeistä ja sen toiminnasta. Etäoperointikeskukseen on myös suunnitteilla kosketusnäyttöjä ja tabletteja, joiden avulla etäoperoijalle saadaan luotua kokonaiskäsitys robotin toiminnasta sekä sen ympäristössä tapahtuvista asioista. Näytöille voidaan tuoda tietoa esimerkiksi laitteiden ja prosessin tilanteesta sekä ympäristössä tapahtuvista muutoksista. Tilannekuvan luomiseen on suunnitteilla hyödyntää erilaisia ratkaisuja esimerkiksi 360^{O} kamera, skanneri ja mobiilirobotti. Mobiilirobotti mahdollistaisi myös vapaamman liikkumisen tuotantotilassa ja esimerkiksi etäläsnäolon ja vuorovaikutuksen paikalla olevan huoltohenkilön kanssa. Lisäksi ympäristössä on 5G verkko.

6 Yhteenveto

Pirkanmaan alueen pk-yrityksille suunnatta PRODI-innovaatioalusta on vielä kehitysvaiheessa. Se on ensimmäinen tälle alueelle Pirkanmaalla rakennettava tämän mittakaavan prosessiautomaation lähtökohdista suunniteltu ympäristö. Tällaiselle juuri tämän automaation osa-alueen tarpeisiin suunnatulle alustalle on todettu olevan tarvetta.

Lisäksi hankkeella on tarkoitus koota alueelta puuttuvaa yritysverkostoa prosessiautomaation parissa toimivista yrityksistä. Vastaavia verkostoja löytyy mm. valmistavan teollisuuden ja liikkuvien työkoneiden yrityksille, mutta prosessiautomaatiolle ei. Koska yritykset ovat hajallaan eivätkä ole vielä löytäneet oman alueensa tutkimus- ja oppimisorganisaatioiden tarjoamaa potentiaalia uusien innovaatioiden kehittämisessä ja testauksessa, on työtä vielä paljon tehtävänä. PRODI-hankkeen puitteissa toivomme saavamme kokoon osan yrityksistä ja jatkamme verkoston rakentamista edelleen seuraavissa hankkeissa.

Tällaisella verkostolla olisi varmasti merkitystä ja tarvetta myös kansallisella tasolla. Suomen laajuisen verkoston rakentaminen on asia, jota on tarpeen pohtia yhdessä muiden alueiden tutkimus- ja oppimisorganisaatioiden kesken. Keskustelua jo toki käydään, mutta konkreettinen aiheen edistäminen vaatii yhteisiä hankkeita.

PRODI-hanke on EAKR-hanke, jonka rahoittajana toimii Pirkanmaan liitto. Hanke rahoitetaan REACT-EU-välineen määrärahoista osana Euroopan unionin COVID-19-pandemian johdosta toteuttamia toimia.

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Effects of Ramp Rate Limit on Sizing of Energy Storage System for PV-Wind Power System

Abstract: The power produced by variable renewable energy power plants (VREPP) can fluctuate heavily and cause issues in the power grid. To prevent the power quality issues in the grid, some countries have set a ramp-rate limit (RR) that the generated output power of power plants may not exceed. The power fluctuations of VREPPs are often mitigated by an energy storage system (ESS) and a power smoothing method. This paper presents how the RR limit value affects the size of an ESS needed for a photovoltaic (PV)-wind power system. Also, the size of the power plant is considered, and how it affects the size of the ESS. The generated power of the PV-wind power system was simulated using measured irradiance, temperature and wind speed. An RR-based control algorithm was used to operate the virtual ESS. It was found that the increase in the RR limit greatly decreases the size of the ESS. The size of the power plant also significantly affects the size of the ESS.

Keywords: photovoltaic power, wind power, power ramp rate, energy storage, power smoothing

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1 Background and Aims

As the amount of grid-connected variable renewable energy power plants (VREPP) increases, the stability of the grid is endangered as the output power fluctuations of these power plants are likely to cause issues with the power quality. Some countries have set limitations in their grid codes to prevent issues caused by highly fluctuating power. For example, Puerto Rico has set a ramp rate (RR) limit of 10 %/min of the rated power of the power plant [1]. The RR limit is the power ramp level below which the power fluctuations of power plants should not cause issues in the grid. The applied RR limits vary by country, and the RR limit of a country can change in the future.

The power output fluctuations of VREPPs are often mitigated by an energy storage system (ESS) and a power smoothing method. The smoothed power acts as the reference power for the ESS. One power smoothing method type is an RR-based control algorithm. An RR-based control algorithm was used in [2, 3] to mitigate the power fluctuations of a photovoltaic (PV) power system. In both studies, it was found that the RR limit value affects the size of an ESS required for the PV power system. There are not that many studies that have investigated sizing of an ESS for a PV-wind power system.

This paper will study the effects of different RR limits on the size of an ESS coupled with a PV-wind power system. Also, it will be covered how the size of the power plant affects the size of an ESS when different RR limits are used.

2 Materials and Methods

Simulations for the generated power of the PV-wind power system were carried out with the irradiance, temperature and wind speed measurements from Tampere University Solar PV Power Station Research Plant [4]. All measurements were done for a period of 5 months with a sampling frequency of 10 Hz. The PV and wind power (WP) was simulated with MATLAB. A virtual ESS was used to mitigate the power fluctuations of the simulated sum power of the PV-wind power system.

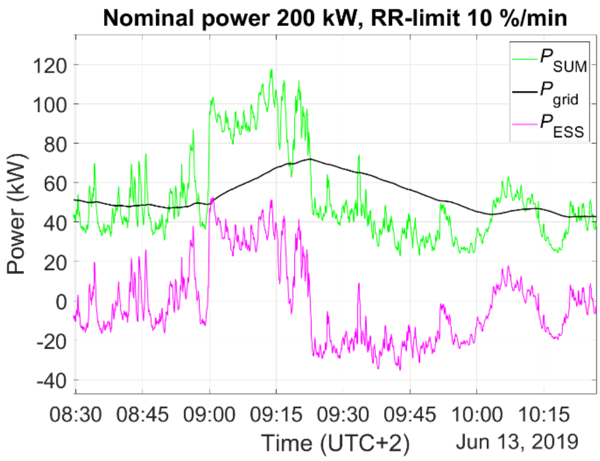

Figure 1: ESS mitigating the fluctuating sum power of the PV-wind power system**.**

The control algorithm used for the ESS was an RR-based algorithm that also takes into account that at every moment the ESS has enough energy for a sudden shutdown of the power plant. In other words, the output power of the power plant follows the RR limit also during a possible shutdown. Fig. 1 shows how the ESS operates to mitigate the fluctuating sum power P_{SUM} of the PV-wind power system. The grid input power of the PV-wind power system P_{grid} does not exceed the RR limit of 10 %/min, as the ESS is either charged or discharged with the power P_{ESS} of the ESS.

The simulations were done for 3 different power plant sizes whose total nominal powers P_{NOM} were 20 kW, 200 kW and 2 MW. With all the power plant sizes, 50% of the P_{NOM} consisted of PV power and 50% of WP. The nominal power of the PV system was scaled using different numbers of PV modules. The nominal power of a single PV module was 190 W. The nominal power of the WP system was scaled using 3 different wind turbine (WT) models whose nominal powers were 10 kW, 100 kW and 1 MW. The hub heights of the WT models were 16.5 m, 19.4 m and 70.5 m, respectively. The measured wind speeds at the height of 16.13 m were extrapolated to the hub heights of the WT models. The applied RR limit values were 1, 2, 5, 10 and 20 %/min with respect to P_{NOM}.

3 Results and Conclusions

The main results of this study are the relative energy capacity $\frac{C_{\mathrm{ESS}}}{P_{\mathrm{NOM}}}$ (Fig. 2) and the relative power $\frac{P_{\mathrm{ESS}}}{P_{\mathrm{NOM}}}$ (Fig. 3) required for the ESS to smooth the power fed to the grid to comply with the applied RR limit all the time. The highest value for the C_{ESS} is mainly determined by the highest value of the P_{grid} as the ESS needs to have enough energy for a possible shut down at the P_{grid}.

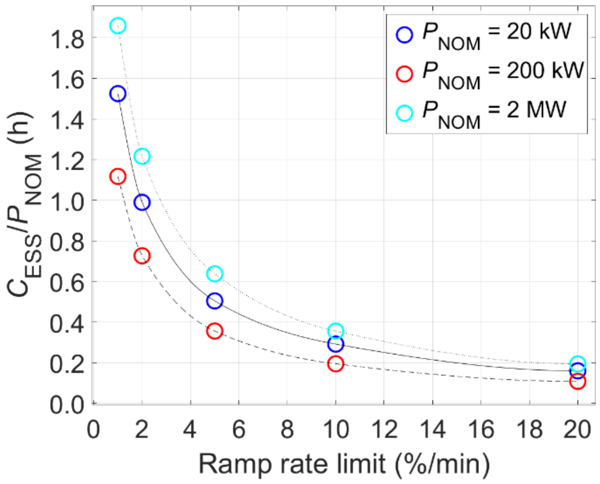

Figure 2: Relation between the ramp rate limit and the required energy capacity of the ESS with different power plant sizes.

In Fig. 2, it can be seen clearly that as the value of the RR limit increases, the value of the $\frac{C_{\mathrm{ESS}}}{P_{\mathrm{NOM}}}$ decreases for all the power plants. As the hub height of the 1 MW WT is roughly 50 meters higher than the hub heights of the 10 kW and 100 kW WTs, the incoming wind speed is higher, and the wind has greatly higher power density at the hub height of the 1 MW WT. This means that there is relatively more power available to be extracted for the 1 MW WT, and thus, the P_{grid} is also relatively higher for the 2 MW power plant. Therefore the $\frac{C_{\mathrm{ESS}}}{P_{\mathrm{NOM}}}$ values are higher for the 2 MW power plant. With the relatively higher generated WP, the power fluctuations of the 2 MW power plant are relatively greater compared to the 200 kW power plant. This explains the higher $\frac{P_{\mathrm{ESS}}}{P_{\mathrm{NOM}}}$ values for the 2 MW power plant compared to the 200 kW in Fig. 3.

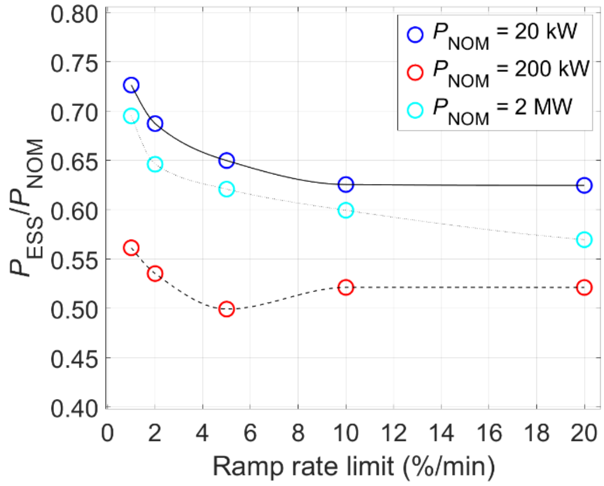

Figure 3: Relation between the RR limit and the power requirement of the ESS with different power plant sizes.

In Fig. 3, it can be seen that as the value of the RR limit increases, the value of the $\frac{P_{\mathrm{ESS}}}{P_{\mathrm{NOM}}}$ decreases for all the power plants. The highest value for the P_{ESS} is determined by the fastest power fluctuation.

As the hub height difference between the 10 kW and the 100 kW WTs is small, the difference between the relative maximum value of P_{grid} is small also. As the size of the PV power plant increases, the output power fluctuations decrease [5]. As the PV power fluctuations decrease, the requirements for the ESS decrease also. In Fig. 2, the $\frac{C_{\mathrm{ESS}}}{P_{\mathrm{NOM}}}$ values of the 200 kW power plant are lower than the values of the 20 kW power plant because the power smoothing effect of the larger PV power plant has a greater impact on the $\frac{C_{\mathrm{ESS}}}{P_{\mathrm{NOM}}}$ values than the increased WP production of the slightly higher WT. This effect also explains why the $\frac{P_{\mathrm{ESS}}}{P_{\mathrm{NOM}}}$ values of the 200 kW power plant are lower than the values of the 20 kW power plant in Fig. 3.

Table 1 shows the highest and median daily requirements for the ESS of the 200 kW PV-wind power system for several RR limits. From the energy shares cycled through the ESS, it can be clearly seen that the ESS operates a lot more during a highly fluctuating day than on an average day. The required size of the ESS is clearly smaller for an average day also.

Table 1. Requirements for the ESS of the 200 kW PV-wind power system for RR limits of 1, 10 and 20 %/min.

	Highest daily value			Median daily value		
RR limit (%/min)	1	10	20	1	10	20
Capacity (kWh)	223	38.9	21.5	107	23.4	13.3
Charging power (kW)	112	104	104	62.7	49.6	49.7
Discharging power (kW)	57.8	75.5	79.7	34.5	43.4	44.5
Energy cycled (%)	35.2	20.2	18.4	25.2	12.0	10.0

The results show that the RR limit greatly affects the size required for the ESS of the PV-wind power system. The size of the power plant has also a notable effect on the size of the ESS.

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Keyword Index