Connected freight rail rolling stock: a modular approach integrating sensors, actors and cyber physical systems for operational advantages and condition based maintenance

Raphael Pfaff[1], Parham Shahidi[2], Manfred Enning[3]

[1] *FH Aachen University of Applied Sciences, Aachen, Germany*
pfaff@fh-aachen.de

[2] *System Sciences Lab, Palo Alto Research Center, Palo Alto, USA*
parham.shahidi@parc.com

[3] *FH Aachen University of Applied Sciences, Aachen, Germany*
enning@fh-aachen.de

Abstract

For decades, the technology of freight railcars has not changed significantly, mostly due to little or no incentive for significant investments in rolling stock. Taking into account the disruptive developments anticipated in automotive transportation, this approach appears no longer feasible, especially if regulatory agencies aim to reduce carbon dioxide emissions while maintaining economic growth. With the advent of telematics, on-board sensing and cloud-based analytics for control and condition based maintenance, high potential for efficiency improvements has become possible. Such technologies are de facto standards in automotive transport, which induces the need for implementation of similar technologies in rail transport as well.

In addition to enabling efficiency gains, telematics, on-board sensing and cloud-based analytics also offer new means to approach pressing problems such as rail noise emission, train integrity and safety against derailment, while at the same time reducing maintenance cost and downtime. Furthermore, a connected wagon offers a seamless integration into current and future logistics systems, which are driven and controlled by the industrial Internet of Things to support the fourth industrial revolution. An important concept, introduced with the Wagon 4.0, is standardized hardware, together with an open-source operating system based on prognostics and health management principles for predictive analytics. Thus, the Wagon 4.0 paves the way for new operations and maintenance concepts, user interfaces and value proposals. Additional economic advantages will be made possible from the self-organizing features of such vehicles, the ability to achieve mass customization and from a rise in efficiency in operation and maintenance. This paper describes the basis of such a system including the power supply, intra-train communications, sensing and cloud-based analytics.

A study of use cases from railway operation illustrates the approach and highlights the opportunities of this novel system design. The paper concludes with a description of how the implantation enables the railcar operator to practice predictive maintenance and increase operational efficiency.

1. Introduction

Transportation of passengers and freight is an important and growing field, for which sustainable modes need to be developed in light of greenhouse gas emission reduction requirements and pressure on operators to reduce costs and increase efficiencies. It is generally agreed that rail transport is one of the more sustainable modes of transportation, while customer choices of transportation mode with respect to sustainability are not yet identified. [1]

The freight rail vehicle sector across the world rarely exhibits technological novelty, especially not in the areas of Internet of Things (IoT) and cloud services, which is deemed a major factor for increasing productivity [2]. Furthermore, the integration of communication technologies into transportation systems is considered an enabler and thus highly required, despite plenty of adoption barriers [3].

While other modes of transportation seek to automate their operations as far as possible, refer to [4], freight rail rolling stock is accepted in its current state and the system has been optimized without considering the potential of selected investments into rolling stock [5].

Another strand of development is that of freight rail telematics systems, which are installed on 85% of trucks in Europe [6]. Such systems are added to the railcar as an isolated system, and transfer the required data directly to its destination without aggregation of data in the vehicle. Notwithstanding the capability of such systems to solve the problem that led to its integration, a deeper integration of individual systems would improve the power of the overall monitoring performance, as proposed in [6].

While these amendments to the freight wagon will provide effective monitoring of the vehicles, their potential for optimization and cost saving is limited with regards to last mile processes, which account for approximately half of the production cost [7].

The integrated and standardized approach of the Wagon 4.0 has the potential to significantly reduce the effort of last mile processes by providing a basis for application specific functionalities. In this study, the requirements for and the concept of the Wagon 4.0 are developed and presented through sample applications for bogie and break performance monitoring.

2. WAGON 4.0 CONDITION BASED MAINTENANCE

Building on top of telematics systems, Condition based maintenance (CBM) is an important aspect of the Wagon 4.0 in order to decrease asset downtimes and to improve the effectiveness of maintenance schedules. Few studies with this scope have been previously completed due to the following reasons:

First, on-board condition monitoring has historically not been applied to freight rail applications and is a new technology in the realm of freight rail maintenance. Typically, condition monitoring in the freight rail industry is achieved through wayside equipment and therefore research in this area has traditionally focused on efficiency improvements. Barke and Chiu [10] published a review of existing freight rail bogie condition monitoring technologies but excluded on-board methodologies and solely focused on wayside technologies. Lagnebck [11] also limited his study of potential cost and efficiency improvements through condition monitoring to wayside techniques, which resulted in recommendations to expand implementation.

Second, most condition monitoring studies have been attempted in the area of passenger rail transport [12],[13]. Due to regulatory safety requirements and the fact that they are a common transportation mode around the world, these systems were historically given more attention than freight rail systems. Differences in mechanical construction, in particular suspension components, and the lack of power on freight systems further complicates the transfer of passenger rail monitoring systems to freight rail systems.

Third, condition monitoring of freight rail applications is not limited to bogies and bogie suspension components. Other areas of interest, where significant work has been completed, include the wheel-rail interface [14], railcar speed inaccuracies due to stick-slip action [15], end-of-car devices [16] and on-board weighing [17] applications which in conjunction ultra-low power monitoring technology was proven to be able to successfully record from accelerometer or straingages.

It is understandable that the emergence of on-board monitoring technologies and continuous improvements in accuracy lead to a vast scope of interest which includes monitoring strategies for components which have traditionally not been able to be monitored effectively.

3. WAGON 4.0: ENABLERS AND DRIVERS

The development of the Wagon 4.0 was initiated by the observation that in most developing countries the freight transport of bulk goods such as coal, oil or gas is set to decrease in the light of the decarbonisation of the energy sector. The total freight volumes will not decrease at equal pace, as an increasing number of smaller items is dispatched. These items are not only smaller, but bear at the same time more value as well as more demanding requirements in terms of punctuality and speed of delivery. For such items, most of the current rail freight systems are deemed unsuitable by the customers, who turn to road transport instead.

3.1. Industry 4.0

The key aspects of Industry 4.0 are mass customization and self configuration. The former term indicates that single, highly specialized items are being produced at the same high efficiency as mass produced articles today, while the latter term expresses the fact that in the factory of the future, machines are expected to organize themselves autonomously, e.g. in the case of failure or maintenance. Driving forces of the fourth industrial revolutions are the Internet of Things (IoT), Cyber Physical Systems and Ubiquitous Computing.

3.2. Condition Based Maintenance

With the high cost of both preventive and reactive maintenance, condition-based maintenance can be considered a key enabler of the Wagon 4.0. Typically, applications follow one of two paths: either that of model-based condition monitoring or that of data driven condition monitoring.

For model-based condition monitoring, a physics-based model, derived from first principles, is used to determine required system parameters. The system parameters are then compared against data to determine if a deviation from a healthy system state is taking place. In [18] this approach was used in a two degrees-of-freedom, half-vehicle bogie model to determine such parameter deviations.

For the data driven case, a signal from the system under test is used to infer what the current system health is. The signal must have a causal relationship to the system component subject to monitoring and thus be indicative of the system's performance. First, the signal is pre-processed and frequency and time domain based features are extracted. In many cases, the number of features can grow large and advanced techniques for selecting those features that are most descriptive are required. Feature selection algorithms include mutual information [19] for estimating the similarity of two signals. The signal features constitute the inputs to machine learning algorithms which attempt to classify the health state of the system. If a target class is specified with the measurements, the problem is classified as a supervised learning problem and if no target class exists, the problem is classified as an unsupervised learning problem. Popular machine learning algorithms include techniques such as neural networks [20] and support vector machines [21] to identify the fault modes from measurements.

In both cases, data is required to either compare against the model or to train the machine learning algorithm. Typically, this data is taken from inertial sensors such as accelerometers and gyroscopes, mounted on the system under test, but other metrics may be used as well. If prognostics is also part of the monitoring strategy, advanced filtering techniques such as particle filters [22] or Kalman filters [23] can be combined with the algorithm to estimate future states from the current state accelerometer measurements.

3.3. Logistics 4.0

As may be expected from the vision of mass customization and self organization, Industry 4.0 will rarely require trainloads of identical material at a given time, but rather smaller amounts of varying goods at the right time. This is well in line with the less recent trends of just-in-time and just-in-sequence logistics, but adds a layer of self-consciousness of the freight and the wagon in order to achieve the ability to be controlled by self organizing machines.

3.4. Wagon 4.0

The problems of the current freight system and especially its rolling stock to fulfill the requirements of Industry 4.0 and Logistics 4.0 call for a concept to innovate wagons on a holistic basis. An approach to this is the conception of a platform to enable extension of the wagon according to the particular needs of a service, similar to smartphone apps.

Such a basis consists of six central elements:

1. Power Supply: Power plays a crucial role in CBM, since freight railcars are typically unpowered assets. It was proposed above to use energy harvesting and to store the generated power in batteries for consumption by the Wagon 4.0. Power efficiency can be achieved by running the monitoring algorithm in an asynchronous, event based mode versus an always-on, continuous monitoring mode.
2. Data Network: The proposed data network shall be considered to consist of a node and gateway system. The nodes will be placed on components of interest and collect the data for upload to the gateway. The gateway can then either use 3G/4G/5G cellular connectivity to communicate the data to a centralized location or utilize an intra-train network to send the data to the locomotive. The locomotive can then seamlessly send the data to the processing point. The advantage of the latter idea is that the locomotive can generate unlimited amounts of power and is therefore able to transmit large volumes of data.
3. Sensors: The sensors of the Wagon 4.0 will be composed of accelerometers and gyroscope sensors with specific characteristics to accommodate the harsh operating environment. This includes features like analog filters to avoid aliasing during data acquisition. Furthermore, digital sensors offer the unique ability to obtain a flat frequency response down to 0 Hz (DC) which is important for collecting data about oscillatory rigid body vibration in fault modes such as *hunting*.
4. Actuators: While sensors and networks provide useful data, the economic effect in the daily operation of the wagon is mainly generated by automating key functions of the wagon, e.g. the brake.
5. Algorithms: The algorithms for condition monitoring have to address a number of machine learning requirements such as data collection, feature extraction, feature selection, classification and prediction in an efficient way. This can be realized by performing the processing on the node level and sending the classification outcome to the gateway in a power constrained situation or sending the raw data to the gateway for processing if energy harvesting is providing adequeate power supply. In both cases, the algorithms have to be designed such that they can compute the desired metrics on low cost hardware in an adequate amount of (i.e. near real-time).
6. Operating System: The so called WagonOS, an open source operating system, will unify the above mentioned four base concepts to allow for extending the capabilities of the Wagon 4.0 and to standardize communication protocolls, data formats and related standards. A central operating system would furthermore enable currently disjointed efforts to unite under the umbrella of a single industry standard.

The provision of these elements for the Wagon 4.0 does not only lead to simplifications for freight customers, it also paves the way to new business models for wagon owners and railway undertakings.

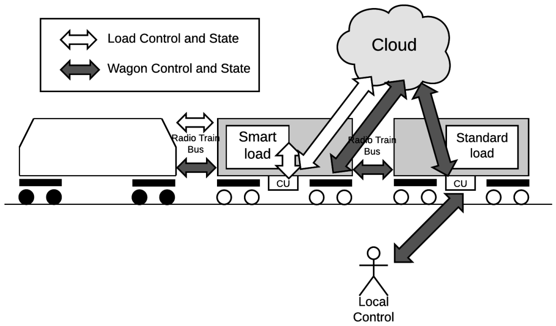


Figure 1. Train concept of Wagon 4.0 and freight

Such business models arise e.g. from the provision of data connection to smart cargo, e.g. high value objects that require monitoring of temperatures and vibration, making the load data another payload of the railway undertaking. The respective connections are depicted in Figure 1.

4. APPLICATIONS FOR PARTICULAR USE CASES

The Wagon 4.0 is set to provide the basis for extensions according to user scenarios or use cases. Numerous discussions have been led with stakeholders in the freight rail system and solutions for different use cases were identified [8, 9]. Of special interest, due to the potential gain in safety as well as economic savings, are condition monitoring of running dynamic properties as well as automation of labor intensive subsystems of the freight wagon, such as the wagon inspection. Also online monitoring of essential train properties can be achieved, with train integrity monitoring being a prominent example.

Another area of increasing interest is the reduction of railway noise emissions, which in Europe has become a limiting factor for the growth of rail transport. Since the advantages of railway noise reduction will mostly support the national economy, no direct incentive for investment is provided in opposition to the former use cases.

4.1. Application Models

4.1.1. Bogie Performance Monitoring

Structured sensor data from components of interest such as brakes, wheels, bearings, and coupling systems as well as oscillation modes such as hunting, pitch, bounce, yaw and roll provide insight into the dynamic behavior of the Wagon 4.0. Previous studies have shown that such an approach can indeed provide the foundation to practice predictive maintenance on a freight rail car. In [24] it was examined how such a system for bogie performance monitoring could be realized with machine learning techniques. The authors utilized sensor data from multiple locations taken on the bogie to gather

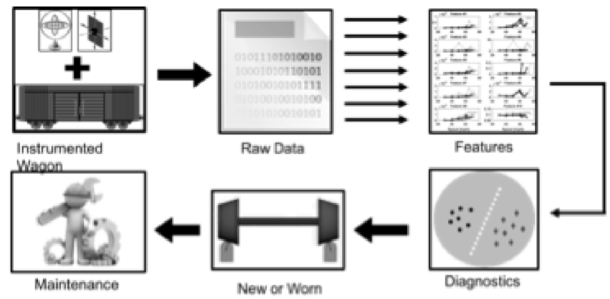


Figure 2. CBM Pipeline

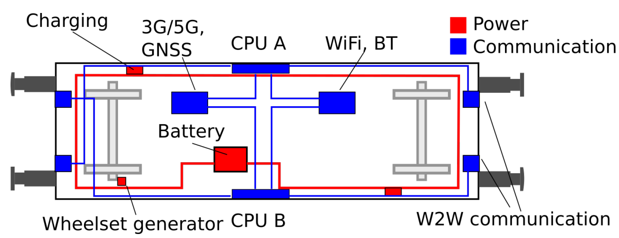


Figure 3. Communication and power network

vibration data in the vertical, longitudinal, and horizontal direction of the wagon. This data was then analyzed in a data processing pipeline which followed the structure explained in section 3.2 for the data driven case. The full data pipeline including an action recommendation as the outcome is shown in figure 2

Once the classifier creates a decision in the fourth step about the wear level of the wheels, an action recommendation can be created and carried out to take the wagon out of service for maintenance at a non-critical time.

The model described above could be considered a proof of concept for the ability to successfully predict the level of wheel wear, the major factor influencing bogie performance in addition to primary and secondary suspension wear, and thus estimate the remaining useful life (RUL) of the wheelset. This information is a key driver in enhancing the planning of maintenance operations.

4.1.2. Train integrity monitoring

In addition to its power supply and wagon monitoring and automation network, as depicted in Figure 3, the Wagon 4.0 also features an intra-train communication network. This intra-train communication network, denoted as W2W-communication, uses two WiFi communication paths at controlled power over directional antennas to avoid misinterpretations of train consists during train formation.

This feature may be used to constantly monitor the train integrity, a task necessary since the safety of railway operation is mainly based on block operation, assuring that upon entrance of a vehicle into a block, it is free from any other vehicle. It is currently achieved by help of infrastructure based wheelset counters. Depending on the density of blocks, a high number of these systems need to be deployed and maintained.

With the movement towards reaching ETCS level 3, the fixed block operation, together with its infrastructure based signals and wheelset counters, will be changed in favour of the more efficient moving block system. This required train based train integrity monitoring, which is comparably easy to achieve for transit applications, especially in multiple units. For the freight rail system, the problem is currently unsolved, however approaches such as [25] exist. These approaches work under the currently valid assumption that freight rail rolling stock is without power supply and thus use battery supplied low power networks for identification of the individual nodes.

While these approaches are generally feasible, the Wagon 4.0 approach is likely to achieve higher acceptance rates, as the train integrity monitoring function is not another system added to the freight wagon but rather an integral part, providing other advantages and thus return on the investment of the wagon holding companies.

The proposed procedure for trains mad up of Wagons 4.0 is to gradually increase the WiFi transmission power during train formation. Thanks to the directed beam of the WiFi-antenna, it only connects to the antenna directly opposite. This information is then used to collect information an wagons in the train including their direction.

During mainline operation, the power of the WiFi transmission is slightly increased to improve reliability of the connection, however it is still low enough to detect the loss of communication after increase of the distance to some meters. Furthermore, all nodes in the train network send continues life signals, which may be also observed by the train integrity monitoring unit in the leading vehicle.

4.1.3. Wagon inspection

The most time consuming single step requiring manual labor in current processes for train preparation is the wagon inspection, shown in table 1 for a freight train of 740 m with 250 axles. The required inspection aspects cannot be defined explicitly, as there exists a large number of combinations of wagons and load.

Due to this, the typical instruction for wagon inspection can only contain a description of which items to check, but is not to be considered an exhaustive check list. Typical items to check are:

1. Closing of all doors, hatches etc.
2. Side and face walls
3. Train gauge
4. Buff and draft gear

Table 1. Comparison of operations required for train preparation

Step	Time current /min	Time Wagon 4.0 /min
Train inspection	39.5	<1.0
Fill Brake Line	40.0	10.0
Condition Assessment	33.2	1.0
Tightness	1.0	1.0
Apply brakes	1.0	1.0
Check brake apply	33.2	1.0
Release brakes	2.0	2.0
Check release	33.2	1.0
Sum	183.1	18.0

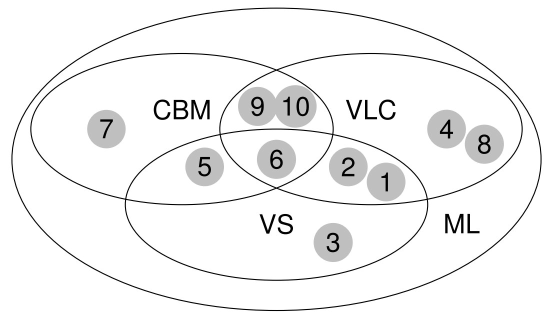


Figure 4. Potential use of information to detect anomalies (numbers refer to inspection items in section 4.1.3)

5. Wheelsets
6. Braking equipment
7. Wagon structure
8. Control elements
9. Pneumatic coupler
10. End cocks

The implicitly defined scope of items to be checked makes the inspection worker in fact a knowledge worker, which is reflected by the fact that for many railway undertaking, the skill level required to perform these inspections is rather high.

With many steps currently being taken to automate knowledge work, it appears sensible to do so also for the wagon inspection, in order to be able to remain competitive with other industries.

We propose to use a combination of volumetric scanning (VS), visible light cameras (VLC) and CBM paired with machine learning (ML) to develop into performing automatic wagon inspection. Due to the safety criticality as well as the comparably small number of samples compared to the possible number of combinations, supervised learning appears to be appropriate for this problem. The anticipated split between the sensing and the inspection items is shwon in Figure 4.

4.1.4. Rail noise monitoring

While the above monitoring tasks generate economic effects the railway undertaking or wagon owning company, the issue of rail noise is more complex. However by appropriate use of the sensors provided for the Wagon 4.0 to achieve the bogie performance and structural monitoring, it is possible to record vibrations of the vehicle structure in a frequency range relevant to rail noise generation.

The main source of noise for freight wagons are the rolling noise, originating from wheel and rail roughness, and noise generated by vibration of parts of the wagons, e.g. the brake rigging. The continuous monitoring of these noise sources can be used in two ways:

- The railway undertaking can make use of the data to plan maintenance as a part of it CBM system.
- The infrastructure manager can use the vibration data of the wagons and their respective geolocalisation to plan and execute rail grinding. This reduces the need for separate inspections of the network.

5. CONCLUSIONS

The idea of the Wagon 4.0 is presented in this paper. The concept of the Wagon 4.0 is unique in that it forms a holistic approach to the problem of monitoring and controlling wagons in the rail freight system.

The main elements of the Wagon 4.0 are:

- Power Supply
- Data Network
- Sensors
- Actuators
- Algorithms
- WagonOS Operating System

Thanks to this holistic approach and the provision of the elements mentioned above, the integration of application specific systems, e.g. for condition based maintenance, rail noise monitoring and wagons inspection, is more economic and also offers additional benefits due to the close integration and standardization of the subsystems.

Three application examples were presented, these are a CBM as well as approaches to the problems of wagons inspection and rail noise. Both show advantages over the use of a traditional wagon, which will help to improve competitiveness of the freight rail system over other transport modes.

REFERENCES

[1] Lammgard C. 2012. *Intermodal train services: A business challenge and a measure for decarbonisation for logistics service providers.* Research in Transportation Business and Management, 5: 48 - 56

[2] Haug K. C., Kretschmer T. and Strobel T. 2016. *Cloud adaptiveness within industry sectors - Measurement and observations.* Telecommunications Policy, 40: 291 - 306

[3] Harris I., Wang Y. and Wang H. 2015. *ICT in multimodal transport and technological trends: Unleashing potential for the future*. Int. J. Production Economy, 159: 88-103

[4] Murgoitio J. et al. 2016. Spanish initiative for fully automated stowage on roll-on/roll-off operations. Transportation Research Procedia, 14: 173 - 182

[5] Marinov M. and Viegas J. 2009. *A simulation modelling methodology for evaluating flat-shunted yard operations.* Simulation Modelling and Practice, 17: 1106 – 1129

[6] Behrends V., Haunschild M. and Galonske N. 2016. *Smart telematics enabling efficient rail transport - development of the ViWaS research and development project*. Transportation Research Procedia, 14: 4430 - 4439

[7] Galonske N., Riebe E., Toubol A. and Weismantel S. 2016. *The ViWaS project: future-proof solutions for wagonload transport.* Transportation Research Procedia, 14: 2850 – 2859

[8] Pfaff R. and Enning M. 2016. *WagonEcosystem: Zeitgeme Automatisierung am Gterwagen.* Bahntechnik Aktuell, 61: 23 - 32 (in German)

[9] Enning M. and Pfaff R. 2016. *Digitalisierung bringt mehr Gter auf die Schiene.* ATZ extra, (accepted for publication) (in German)

[10] Barke, D. and Chiu, W.K., 2005. *Structural health monitoring in the railway industry: a review.* Structural Health Monitoring, 4(1), pp.81-93.

[11] Lagnebck, R., 2007. *Evaluation of wayside condition monitoring technologies for condition-based maintenance of railway vehicles*. Lule: Lule University of Technology.

[12] Ward, C.P., Goodall, R.M., Dixon, R. and Charles, G., 2010, September. *Condition monitoring of rail vehicle bogies.* In Control 2010, UKACC International Conference on (pp. 1-6).

[13] Ward, C.P., Weston, P.F., Stewart, E.J.C., Li, H., Goodall, R.M., Roberts, C., Mei, T.X., Charles, G. and Dixon, R., 2011. Condition monitoring opportunities using vehicle-based sensors. *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, *225*(2), pp.202-218.

[14] Hubbard, P., Ward, C., Goodall, R. and Dixon, R., 2013. Real time detection of low adhesion in the wheel/rail contact. *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, p.0954409713503634.

[15] Mei, T.X. and Li, H., 2008. Measurement of vehicle ground speed using bogie-based inertial sensors. *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, *222*(2), pp.107-116.

[16] Hopkins, B.M., Seidel, A., Maraini, D. and Shahidi, P. 2015. March. *End-of-Car Device Condition Monitoring With Onboard Sensors.* In 2015 Joint Rail Conference (pp. V001T06A005-V001T06A005). American Society of Mechanical Engineers.

[17] Maraini D., Shahidi P., Hopkins M., and Seidel A. 2014. *Development of a Bogie-Mounted Vehicle On-Board Weighing System.* In 2014 Joint Rail Conference, pp. V001T02A001 -V001T02A001. American Society of Mechanical Engineers,

[18] Li, P. and Goodall, R., 2004, September. Model-based condition monitoring for railway vehicle systems. In *Proceedings of the UKACC international conference on control, Bath, UK*

[19] Maraini, D. and Nataraj, C., 2015. Freight Car Roller Bearing Fault Detection Using Artificial Neural Networks and Support Vector Machines. In *Vibration Engineering and Technology of Machinery* (pp. 663-672). Springer International Publishing.

[20] Haykin, S. and Network, N., 2004. A comprehensive foundation. *Neural Networks*, *2*(2004).

[21] Cortes, C. and Vapnik, V., 1995. Support-vector networks. *Machine learning*, *20*(3), pp.273-297.

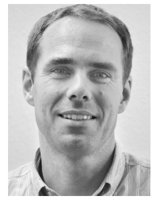
[22] Arulampalam, M.S., Maskell, S., Gordon, N. and Clapp, T., 2002. A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking. *IEEE Transactions on signal processing*, *50*(2), pp.174-188

[23] Kalman, R.E., 1960. A new approach to linear filtering and prediction problems. *Journal of basic Engineering*, *82*(1), pp.35-45.

[24] Shahidi P., Maraini D., Hopkins B. and Seidel A. 2015. *Railcar Bogie Performance Monitoring using Mutual Information and Support Vector Machines.* Annual Conference of the Prognostics and Health Management Society, Coronado, California. 2015.

[25] Scholten, H., Westenberg, R. and Schoemaker, M. *Trainspotting, a WSN-based train integrity system.* Eighth International Conference on Networks. Gosier, Guadeloupe, France. 2009.

BIOGRAPHIES



Raphael Pfaff was born in Hagen, Germany in 1977. He pursued studies in Mechatronics (FH Bochum, Germany, Dipl.-Ing. (FH) 2006), Mathematics (FeU Hagen, BSc 2007) and Control Engineering (Coventry University, UK, MSc 2006, PhD 2013). He worked with Siemens and Faiveley Transport as System Engineer and Engineering Manager before receiving the call for his current position as Professor of Rail Vehicle Engineering at FH Aachen. His research interests include digitisation of railway rolling stock, reliability engineering and big data usage as well as wheel-rail contact modelling. He is scientific advisor to the Interdisciplinary Railway Research Network (IfV Bahntechnik) as well as member of German Mathematical Society (DMV) and German Rail Engineering Society (DMG).

Parham Shahidi holds a Ph.D. in Mechanical Engineering from Virginia Tech, where we worked at the Center for Vehicle Systems and Safety, and a B.S. in Mechanical & Process Engineering from TU Darmstadt in Germany. He has served as an adjunct professor at Virginia Commonwealth University, and is a board member of the German Engineers Association (VDI) in North America. His major projects include the development of machine learning algorithms for vehicle instability detection, wheel wear prediction, onboard weighing and bearing condition monitoring. He is an active contributor to professional organizations including ASME, VDI, JVC and the PHM Society. In 2015 he received the Best Technical Paper Applied award of the Prognostics and Health Management Society.

Manfred Enning holds a Dr.-Ing. in Control Engineering from RWTH Aachen University as well as Dipl.-Ing. in Mechanical Engineering also from RWTH Aachen University. Prior to accepting the call upon a professorship for railway systems engineering at Aachen University of Applied Sciences, he worked in several roles at Institute for Control Engineering (IRT) of Aachen University. His research mainly focuses on automating and powering freight rail rolling stock as well as the potential impact of new technologies on railway operations. He contributes to the German Engineers Association (VDI) as member of the professional advisory board for railway systems.