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Smart Gravel or Smart Wireless Sensors in Rail: A Comprehensive Review

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In this paper, we explore the use of wireless smart sensors in railway systems, focusing on the concept of ”smart gravel” - a system that embeds wireless sensors within the ballast to monitor track conditions. We first provide an overview over the landscape by highlighting reviews from other authors on the topic. We then explore the topics embedded AI, and energy harvesting in the rail domain by reviewing existing literature. Following we are discussing works from other authors which came the closest to realising the idea of smart gravel. Through a comprehensive review of the existing literature, we identify the key challenges in the field, including the need for open datasets in research, more and longer field tests and the adoption of MEMS sensors in the railway industry. Possible research gaps according to our findings are the development of dependable smart gravel systems as well as bringing federated learning into the picture for railway monitoring.

Keywords: Smart Gravel, WSN, preventive maintenance, autonomous rail operations, decision support systems, MEMS.

1. Introduction

Railway systems are essential for freight and passenger transport, providing a sustainable alternative to road travel (Singh et al. (2022)). However, increasing traffic and network expansion challenge infrastructure safety. Tracks, ballast, and substructures degrade due to wear, environmental stress, and usage. Early fault detection prevents accidents, reduces costs, and extends railway lifespan (Phusakulkajorn et al. (2022)). Wireless sensor systems offer solutions beyond predictive maintenance, including fault detection, train arrival warnings, and crossing security. This paper examines the potential, capabilities, and limitations of wireless smart sensors in railway systems.

1.1. *Smart Gravel*

Wireless technologies simplify railway monitoring by replacing cables and reducing maintenance complexity. One innovative approach is ”smart gravel”, embedding wireless sensors in ballast to monitor pressure, vibrations, and track movements (Fraga-Lamas et al. (2017)). These sensors are designed for easy placement without fasteners.

While smart gravel remains a technological challenge, this paper reviews key enablers such as low-power wireless communication, embedded AI (Artificial Intelligence), and energy harvesting. Relevant literature and the current state of the art are discussed.

In this review, we are focusing on the following research questions:
1. Which demonstration cases exist in the scientific literature which can act as a role model for Smart Gravel?
2. Which AI techniques are successfully used in trackside applications in the rail sector?
3. Which ways to power sensor nodes on the rail track are successfully used in which applications in the rail sector?

1.2. *Methodology*

This review focuses exclusively on articles from the railway domain that address trackside sensors, excluding sensors installed on rolling stock. To make sure we have an overview over the topic we begin by discussing related reviews. Their niches, structure and main findings are compared and issues they found in their reviewed works are discussed. In the subsequent chapter, publications from the rail sector that integrate AI into trackside sensors are analyzed based on their goals, major achievements, and challenges faced. Following that, the next chapter examines Energy Harvesting solutions, comparing them in terms of their energy output in a rail scenario. The final part of this review is dedicated to examining existing articles that have attempted to develop systems similar to the concept of smart gravel. These works are also compared using the criteria already mentioned (objective, key achievements and encountered challenges).

We will not take into account aspects like data compression and communication (protocols), although for the idea of smart gravel it is important.

2. Related Reviews

Several reviews have come up in the last years concerning the concepts of Smart Gravel. A few of them should be named here to give an overview and resource for further reading. Some are more concentrating on the high level view, some more on the energy supply, they combined give a good picture about the foundation works for the smart gravel concept. The overview can be seen in table 1.

However, to the best of the authors' knowledge, there is a lack of a structured review specifically focusing on the concept of smart gravel. This paper aims to fill this gap by providing a comprehensive review of the core components of smart gravel, including AI, and energy harvesting, in the following thereby named chapters.

2.1. *AI*

In the reviewed works concerning the application of AI (an overview can be seen in table 2), there is significant interest in detecting track-related events, such as ensuring track clearance to safeguard crossings and warning of approaching trains. Predictive maintenance is also a key focus, as it is more feasible for a rail network operator to equip the network with sensors for detecting defective rolling stock than to equip each train individually with sensors.

The reviewed articles cover a range of data sources, including acceleration data, audio data and strain gauge measurements. The majority of studies employed acceleration data for classification purposes, frequently using Support Vector Machines (SVMs) due to their efficient inference and Neural Networks for their generalization capabilities.

The use of preprocessing techniques like Gramian Angular Fields and Wavelets for defect detection (Krummenacher et al. (2017)) and the application of Fast Fourier Transforms for train detection (Ardiansyah et al. (2018)) were employed to enhance classification performance. As a Smart Gravel device is constrained in the available computing resources, these feature engineering techniques can play a crucial role in enabling AI-based railway monitoring.

2.1.1. *Challenges*

Many studies, such as those by Krč et al. (2020), Lee et al. (2016), and Ardiansyah et al., faced the challenge of small datasets, which limit the generalization of their results. This issue is exacerbated when data is only gathered from a single location, as seen in the works of Saputro et al. (2022) and Ardiansyah et al. This can also serve as an explanation of the claimed accuracy of 100% in the works of Ardiansyah et al. as this could be credited to overfitting then.

While AI techniques in railway monitoring show significant promise in the lab, they are still hindered by the availability of datasets. Most of the authors of the papers examined in this work had to create their own dataset due to a lack of openly available datasets. To the best knowledge of the authors there are no openly available datasets of trackside one dimensional data for railway monitoring available.

The periods for testing the approaches in all the reviewed articles were very limited, often only for a few hours. This is another hurdle which limits the generalizability of the results. To develop dependable monitoring equipment it is necessary to test it over a long period of time and in different

Publication (Review)	Niche of Review	Structure	Main findings	Issues pointed out
Hodge et al. (2014) Wireless sensor networks for condition monitoring in the railway industry: A survey (Hodge et al. (2014))	Condition Monitoring in the Railway Industry using Wireless Sensor Networks, emphasis on practical engineering solutions.	divides between fixed (on infrastructure) and movable (on rolling stock) monitoring approaches; gives an overview about sensors used for railway condition monitoring	points out that there are still issues in routing and energy supply especially in inaccessible locations	
M. Bosso et al. (2021) Application of low-power energy harvesting solutions in the railway field: a review (Bosso et al. (2021))	Explores low-power energy harvesting techniques for powering sensors in rail applications	divides between sources of energy (vibration, electromagnetic, thermal, wind, solar), further by trackside or movable	most successful source of energy in rail environments is vibration; piezoelectric and electromagnetic harvesters are a solution, but they have to be tuned to the corresponding frequencies	efficient energy storage systems are still a challenge; geared devices should be avoided to provide longevity
Castillo-Mingorance et al. A critical review of sensors for the continuous monitoring of smart and sustainable railway infrastructures (Castillo-Mingorance et al. (2020))	Reviews and compares sensors for predictive maintenance of railway infrastructure to prevent failures,	Presents Strain Gauges, Piezoelectric Sensors, Fiber-Optic Sensors, Geophones and Accelerometers; discusses case studies in which each of them were used and discusses their pros and cons.	Strain gauges and optical fiber sensors provide very accurate results, however they are costly; Piezoelectric sensors and accelerometers are cheap and accurate; Best fit for track monitoring are piezoelectric, accelerometer or fiber optic sensors	High costs for advanced sensors; sensors need to be economically viable and technically robust; durability and resilience to environmental factors is still an issue (e.g., electromagnetic interference, temperature changes, vandalism).
Fraga-Lamas et al. Towards the Internet of smart trains: A review on industrial IoT-connected railways (Fraga-Lamas et al. (2017))	High Level survey of relevant technologies for smart railway infrastructure, including safety systems.	Discusses Communication Systems in and around trains as well as in infrastructure, gives and overview over GSM-R and from that introduces LTE-R, the successor; Proposals for more efficient Operations to New Business Models are given;	LTE and IoT technologies are transforming railways with improved safety and operations; Key applications include predictive maintenance, smart infrastructure, and advanced monitoring.	Smart Railways are challenged by the lack of standardization, interoperability and scalability issues, energy efficiency and the thread of cyber security

Table 1: Overview of Related Works

locations making sure the results are stable.

2.2. *Energy Harvesting*

In this section we will look at the different ways to power the sensor nodes. At the end of this section, table 3 shows an overview of the considered harvesting methods in an example scenario.

Only trackside methods with zero moving parts are considered here to maximize longevity. Triboelectric harvesters and acoustic harvesters are excluded for now for space reasons but will be included in a later publication. Calculations for piezoelectric and electromagnetic harvesters are first estimates, depending on train speed and weight.

2.3. *Piezoelectric Energy Harvesting*

Piezoelectric harvesters convert mechanical vibrations or pressure into electrical energy; rail-bed mounting is common. These harvesters (al well as electromagnetic ones) generate electricity only when trains pass, which can be expressed as

$$n_{\text{activations}} = n_{\text{trains}} \cdot n_{\text{axles}} \tag{1}$$

Literature shows a wide range of power outputs. Bosso et al. (2021) list railside devices from $150\,\mu$W to 588 mW, Qi et al. (2022) list from 119 mW to 39.1 W. Many works provide peak power with limited field data. Tianchen et al. (2014) harvested 2.08 mWs (lab scale, 16 transducers). Wischke et al. (2010, 2011) measured 260–395 μWs on real tracks. Differences arise from train types, lab vs. field conditions, and rail environments. Shan et al. (2023) demonstrated a high-power, robust piezoelectric stack energy harvester that converts track vibrations into electrical energyclaiming to providing a sustainable power source for wireless sensor networks (WSNs). However the authors did not provide any information about the the expected energy return by a passing train, which would be very useful for the design of a Wireless Sensor Network (WSN) powered with this harvester.

2.4. *Electromagnetic Energy Harvesters*

Electromagnetic harvesters use a magnet-coil arrangement to generate electricity from rail vibrations. Hou et al. (2018) report 257 Ws per

Publication	Objective	Key Achievements	Challenges
Krč et al. (2020)	Neural network-based train type identification (5 classes) using accelerometer data from switches and crossings (S&C) recorded with a cheap Accelerometer (ADXL345)	Classification was possible, accuracy up to 80%; Paper showed that CNNS deliver the best results and can generalize the identification problem of train types in switches and crossings to other locations	Small datasets (two locations) and sensitivity to noise; author proposes more sophisticated architectures; better results are expected with more data.
Lee et al. (2016)	Developing a cost-effective method for detecting and diagnosing faults in railway point machines using audio data; test their setup by different simulated errors on their testbed. Uses MFCC and SVNs for classification	Classification was possible but with a very small dataset. Accuracy up to 97%	dataset too small; dependent on the position of the microphone;
Saputro et al. (2022)	They developed a train detection system to verify clear tracks. IMU data and a neural network was used and the system was tested in a real rail environment. With this work they want to avoid shortcomings in axle counters and track circuits which the mainly used method of train detection nowadays.	They showed that classification of IMU data in an embedded rail environment is possible. With a BNO055 IMU and a raspberry pi they archived a 94% accuracy	Detection is not accurate enough for production, data was only gathered from one location. Only a html page of their work is available, images are missing, which makes understanding their work hard.
Ardiansyah et al. (2018)	Build a warning system for an approaching train for safeguarding railroad crossings without guards. For that they used an accelerometer, a Fast Fourier Transform and a Neural Network	They claim to archieve 100% accuracy of detecting an approaching train with a distance of 45 meters; they give examples of vibration patterns for cars, trains motorcylces and trucks	Dataset is extremely small (small two digit number). Also they measured at only one location, so there is little generalization possible
Krummenacher et al. (2017)	Developed classifiers for defect detection on railway train wheels using SVMs and DNNs and by modeling the multi sensor structure of the datasource; Strain gauges were used for measuring a signal of a passing train	They build their own dataset in cooperation with the swiss train operator SBB and did tests on artificially damaged wheels; GAF (Gramian Angular Fields) and Wavelets were used as preprocessing; Their system was intended for deployment in the Swiss railway network.	Data labelling was a problem. As the data was from the field, it was not always clear under which circumstances it was recorded (e.g. orientation of the wheel).

Table 2: AI Techniques:Overview of Publications in Railway Monitoring

passing metro train (bridge setting). Gao et al. (2018) report mean and max power of 45.5 mW and 550 mW, respectively, with a train pass taking 0.375 s per wagon at 250 km/h. Calculating per axle yields about 17.63 Ws. For a 12-car train, that corresponds to 819 Ws, which is lower than Hou et al.'s 3084 Ws Hou et al. (2018) but provides a realistic range.

2.5. *Thermal Energy Harvesters*

Thermoelectric harvesters rely on the Seebeck effect, using the temperature gradient between rail and ballast. Gao et al. (2019) report a maximum of 5.8 mW for an 8 °C gradient in field tests, producing about 46 mWh/day for 8 h of such a gradient. Seasonal and regional variations limit this technique's reliability.

2.6. *Photovoltaic Harvesters*

PV cells can provide > 25 mW/cm^2 under optimal conditions Shen et al. (2024), but output is highly variable and subject to dust pollution. Using PVGIS European Commission (2023) data for northern Germany (lowest solar months Nov–Jan) yields about 29.2 kWh/kWP in three months. This implies a sensor must not exceed 29.2 Wh per installed Wp in that period. Dust accumulation on trackside PV (about 1.369 g/m^2/year over a decade) can cause up to $\sim$34% power loss Lorenzo et al. (2007); Hachicha et al. (2019); Chen et al. (2019); Hussain et al. (2017). Trackside pollution from train operations exacerbates this effect.

Harvesting Technique	Total Energy Estimation
Piezoelectric Energy Harvesting	130 - 395 μWs per axle
Electromagnetic Energy Harvesting	819 Ws (12-car train)
Thermal Energy Harvesting	208.8 Ws per day
Photovoltaic Energy Harvesting	288 Ws/WP per day

Table 3: Energy Estimations from Literature for different Harvesting Techniques

A publication by the authors of this work is currently under preparation, providing a detailed review of energy needs and harvesting possibilities for small trackside sensors. This paper will include a method to estimate pollution at a rail line and its impact on solar performance.

2.7. *Contributions near to the concept of "Smart Gravel": Using MEMS Sensors for rail infrastructure monitoring*

MEMS (Micro-Electro-Mechanical Systems) accelerometers have been extensively used to measure vibrations and dynamic behaviors in railway tracks, an overview of the most important works of the last years can be seen in table 4. For example, Milne et al. (2016) demonstrated the successful use of MEMS accelerometers like the ADXL335 and ADXL326 to detect track displacements during passages of rail cars. They compared the cheap MEMS devices with state of the art piezoelectric sensors and geophones in lab test as well as in a field test. Results indicate that the frequency and amplitude of vibrations agree between MEMS accelerometers and piezoelectric sensors / geophones. Their study highlighted the ability of these sensors to operate at low power while delivering highly accurate data regarding track behavior under various loads and be very robust in the same time. As the scope of the authors was just the comparison, they did not have a use case for the measurements in their study.

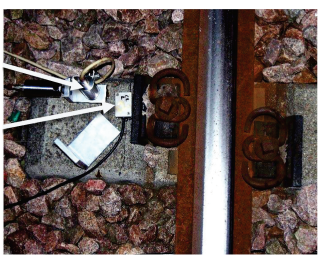

Fig. 1. Comparison of MEMS accelerometers and geophone done by Milne et al. Milne et al. (2016).

Similarly, Stenström et al. (2017) tested ADXL326 accelerometers in heavy haul railway settings by building a prototype for a smart sensor. They demonstrated that MEMS technology can effectively measure sleeper displacement under train axle loads, providing reliable data for condition-based maintenance. However his prototype was just for data aquisition, not for classification of the acceleration data. The study showed promising results in measuring displacements, aligning with laboratory tests and existing literature. However, the paper could benefit from providing more information on the methods and results.

Berlin and Van Laerhoven (2013) did a study on the vibration patterns caused at the rail track by passing trains. They used a WSN to monitor trains by analyzing vibrations caused by their movement along railway tracks. Small, robust, and inexpensive sensor nodes were deployed on the tracks, equipped with 3D accelerometers to capture vibration data. The nodes processed the data locally using features like vibration duration, amplitude, and patterns. These features were used for a classification of train types and estimation of train lengths with a Support Vector Machine (SVM), achieving a high accuracy of up to 97% according to the authors. They also came to the conclusion that there is potential to estimate the train speed and detect worn-out cargo wheels, however the scope of the study was not including showing that. What is to note is that they only measured at one location, meaning they would not have seen different data characteristics due to different soil conditions.

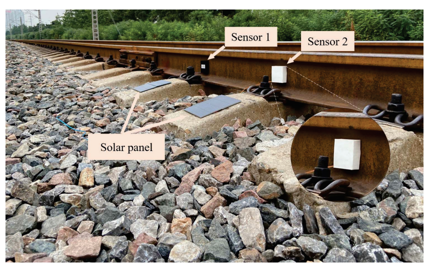

Fig. 2. Prototype for train monitoring done by Zhao et al. (2021).

Zhao et al. (2021) extended the work of Berlin et al. by developing a system to continuously monitor train parameters such as speed and the number of carriages also using a MEMS-based accelerometer. The sensor was placed on the rail to capture vibration data caused by passing trains.

This data was processed locally using a Fast Fourier Transform and a careful selected set of features by which the speed of the train could be estimated. Their paper features an extensive comparison between different equipment to use in the sensor nodes and their impact on the power consumption, e.g. microprocessors, communication chips and sensors. Their work also provides a justification for the choice of sampling rate for an accelerometer mounted on the rail, recommending a minimum of 3.2 kHz. However the authors had special knowledge about the trains running on the track and did only measure in one specific location. The possibility of other signal properties because of other nature of the soil was excluded in their work. They also excluded interferences with other rail lines by placing the sensors on positions where the distance to the next rail line is maximal. Also their requirements were that "it was required that the rail at the sensor position be free of obvious damage, cracks, and pollutants, that fasteners be of normal tightness, that sleepers do not sink, and that the position be normal." The processed results are transmitted to a cloud server via a low-power NB-IoT network. A solar-powered module ensures the device operates continuously without external power, however they did not go into detail about the feasibility of solar energy harvesting yeararound nor did they address the potential impact of pollution on the solar cells. This publication is to the best of the authors knowledge the closest to the idea of smart gravel up to now.

3. Conclusion

In conclusion, the concept of Smart Gravel has the potential to revolutionize railway monitoring and maintenance practices. Our review of the literature has highlighted key technologies, including AI techniques and energy harvesting techniques. We have also identified the challenges and research gaps in the field, including the availability of datasets, the missing adaptation of MEMS sensors in industry, and the need for long-term tests.

The use of AI techniques in track-side monitoring has shown significant promise, with applications in detecting track-related events, such as ensuring track clearance to safeguard crossings and warning of approaching trains. However, the reviewed articles have also highlighted that more openly available datasets are needed for training and testing AI models. Also, the tests in the field should be held longer to get an idea of the challenges of smart gravel systems in long term deployment.

In terms of energy harvesting, we presented the most promising techniques, including piezoelectric, electromagnetic, thermal, and photovoltaic energy harvesting. Notable is the steady output of power by thermoelectric harvesters and the high yield but also high variance o photovoltaic harvesters. Piezoelectric and electromagnetic harvesters are promising for rail monitoring. However, they often need to be tuned to specific vibration frequency ranges, which are not always steady in the real world, further highlighting the need for longer field tests.

3.1. *Research Gaps identified*

A research gap is believed to be existent concerning the dependability of smart gravel systems. In the long run, it is possible that information from WSNs in the field play a role in decisions which can harm passengers (e.g. dependable localization of trains). To address this need, smart gravel or WSNs in general can be viewed as a safety relevant system. This poses significant requirements to the sensor nodes and the network as a whole especially if AI is involved. To the best of the author's knowledge no article focussed on this was published so far. To navigate these waters can be of interest to the next years of research in the field.

Another research gap is believed to be in the connection of smart gravel and federated learning. It has become clear from this review that all the works carried out currently were training and testing their algorithms at data from one specific location. From other disciplines (e.g. geology) it is known that the propagation and reflection of seismic waves differ from one type of soil to the other. This makes it substantially harder to train a classifier, e.g. for train localization, which works on train tracks at all locations. The concept of federated learning can help here while keeping the advantage of independent sensors alive, eliminat-

Publication	Objective	Key Achievements	Challenges
Milne et al. (2016)	They want to provide evidence for the use of cheap MEMS accelerometers instead of expensive geophones and piezoelectric sensors by doing laboratory tests as well as field tests.	Demonstrates MEMS accelerometers are suitable for cost-effective track displacement and vibration monitoring by comparing them with high quality sensors; Also did further field tests by comparing a cheap MEMS accelerometer with a geophone; results show that cheap MEMS accelerometers and geophones aggree on frequency and amplitude, however the MEMS accelerometer is noisier; MEMS accelerometers can be used instead of a geophone for trackside monitoring	Field test was not carried out over longer periods; MEMS accelerometer is noisier; Scope of the study was just the comparison, so no use case for the measurements in their study;
Stenström et al. (2017)	measured sleeper displacements with ADXL326 accelerometers in heavy haul railway including building a prototype.	provides valuable information for building a smart sensor system, including comparison of different MEMS accelerometers and Microcontrollers and a discussion on timing regarding data gathering; provides a discussion about power usage in a smart sensor including the use of a wake-on-shake module in the prototype; Field tests indicate that cheap MEMS sensors can be used for rail monitoring.	Field test was not carried out over longer periods, therefore the results are not analysed regarding temporal artefacts; no analysis or classificationdone on the sensor, just data gathering
Berlin and Van Laerhoven (2013)	Monitor trains via vibration analysis using Wireless Sensor Networks (WSNs) on rail tracks. Classify train types and estimate train lengths.	Deployed robust and inexpensive sensor nodes with MEMS accelerometers; Local data processing using vibration features (e.g., duration, amplitude); Achieved up to 97% classification accuracy using Support Vector Machine (SVM).	Measurements were limited to a single location, reducing generalizability; e.g. not addressing the impact of varying soil conditions; Potential capabilities (e.g., speed estimation, worn-out wheel detection) were noted but not demonstrated. Zhao continued the work.
Zhao et al. (2021) Continuous Monitoring of Train Parameters Using IoT Sensor and Edge Computing	Extended the work of Berlin et al. by developing a system to continuously monitor train parameters (speed, number of carriages) using a MEMS-based accelerometer and vibration data from the rail.	showcased that solar powered MEMS accelerometers could be used for continuous monitoring of train operation. Comparison between different equipment to use in the sensor nodes and their impact on the power consumption, e.g. Microprocessors, communication chips and sensors; Their work features a reasoning for the choice of the sampling rate for an accelerometer mountes to the rail (min 3.2 kHz)	Their test was only for 24h; they did not cover running the node on solar all year long or the impact of pollution on the solar cells; They need special knowledge about the trains running on the track and did only collect data at one specific location.

Table 4: Overview of publications on using MEMS Sensors for railway monitoring

ing the need for retraining.

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