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AN ELEVATOR CALIBRATION RECOMMENDER SYSTEM FOR EFFECTIVE DEFECT DETECTION AND PREVENTION

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Abstract. Machine Learning and Recommendation Systems (RSs) have had a significant impact on the manufacturing industry, heralding in the smart manufacturing era of Industry 4.0. An RS is a class of machine learning that recommends items from a knowledge base utilizing data filtering and analysis. RSs are designed to assist employees in making decisions, by improving their capacity to recognize the optimal option from a variety of alternatives. This work describes a Deep Neural Network model, inspired by the collaborative filtering and factorization matrix approaches, trained using an elevator manufacturing company's dataset of the elevator hydraulic press calibration unit test over a two-year period. The proposed model aims to provide the company's operators with predictions about target parameters during the hydraulic press calibration process (i.e., speed, pressure) in order not to exceed a maximum level of noise. It predicts speed and pressure with a Mean Squared Error of 0,0015 and 0,0078, respectively. Furthermore, Pearson Association Coefficients were calculated for all validation runs, showing that the predictions were highly associated with their actual values.

Keywords: Recommendation System, Deep Neural Networks, Zero Defect, Smart Manufacturing, Industry 4.0.

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1 INTRODUCTION

Production of high-quality goods and products is at the centre of today's manufacturing sector. Manufacturers strive to create products with zero flaws, which necessitates the application of comprehensive quality control procedures at every stage of the production process. In this context, Machine Learning (ML)-based solutions have become a potent tool for facilitating Zero Defect Manufacturing (ZDM). Applications called Recommendation (or recommender) Systems (RS), evaluate data and make suggestions to users about items from a knowledge base. RSs have become an essential component of smart manufacturing, thanks to the application of artificial intelligence (AI) techniques. RSs provide operators with useful guidance on how to modify the production line to reduce errors, by analyzing and reasoning over data that is related to recognized abnormalities and suboptimal operations in the production line.

Particularly, RSs produce suggestions to users based on filtering and analysis of data [1]. As such, the use of AI techniques, such as computational intelligence and ML, is significantly pronounced in the development of RSs [2]. Hence, RSs can constitute an important feature towards ZDM, aiming at providing helpful information to the operators on how to timely adjust the production line in order to avoid defects caused by suboptimal manufacturing environment conditions (such as machine calibration parameters). Such systems can be trained on data pertaining to past actual configurations that don't impose anomalies and known suboptimal operations in the production line, and realize the detection of both existing and potentially upcoming defects. In this way, they can calculate equipment parameters readjustments in real-time, thus effectuating the automation needed to overcome problematic situations effectively and efficiently.

RSs (and the ML field in particular) have had a huge influence on the manufacturing industry, making conventional manufacturing processes "smarter", a key characteristic of the Industry 4.0 era [3]. In this paper, we conduct a comprehensive investigation of ML-based RSs to enhance shop floor operator decision-making with respect to production line calibration. Our aim is to gather valuable insights that can be utilized to implement just-in-time system re-configuration techniques, and identify similar approaches. To illustrate the effectiveness of ML-based RS, we describe a recommendation ML model developed for an elevator manufacturing company, which focuses on optimizing the configuration of the hydraulic press for proper elevator ascending and descending. The proposed model is trained, validated, and tested on a dataset of 7,200 valid elevator configurations, with a split of 60%-20%-20% respectively. The results of this study demonstrate the potential of ML-based RSs for improving quality control measures in the manufacturing industry.

2 RECOMMENDATION SYSTEMS IN MANUFACTURING

AI plays a huge role, as an up-and-coming technology in ZDM I4.0 reference architecture compliant solutions [4]. Hence, RSs have been used widely in smart manufacturing applications. Nikolakis et al. [5] proposed a two-level Collaborative Filtering RS for training a Production Line Operator (PLO), taking into consideration the PLO's feedback [6]. A K-

Nearest Neighbours algorithm extracts a list of PLO profiles similar to the target's, as well as instruction sets that were ratted higehr by PLOs with similar profiles. In [7], a unique deep learning-based multi-criteria collaborative filtering approach is presented. This model consists of two parts: the first portion gathers data about individuals and products to feed into the Deep Neural Network (DNN) that predicts how those features will be rated on the criteria. The second component, a DNN trained to predict an aggregate rating, takes the aforementioned criteria ratings as input.

Regarding the personalized recommendation for Manufacturing Service Composition (MSC), a hybrid PoNSGA-III & Clustering-based Collaborative Filtering algorithm has been developed [8]. By taking both the Quality of Service (QoS) goal attributes and the customer choice attribute into account, a multi-attribute customized recommendation is formulated as a search for the best MSC items for the manufacturing task chain. The proposed algorithm uses a rating of customer preference characteristics to provide the best options for a given client. Another hybrid algorithm for QoS prediction was proposed in [9]. More specifically, the combination of similarity-enhanced collaborative filtering and improved case-based reasoning in an ensemble model is used, to establish a hybrid QoS prediction framework for cloud manufacturing. Resource similarity models for autonomous resource filtering leverage RSC's decision-making process, and push the best-suited resource to the host. The interaction model allows self-organized, human-free manufacturing.

On the other hand, Human-Machine collaboration is highly prominent in smart factories that strive to leverage the strengths of both knowledge workers and smart manufacturing technologies (such as AI/ML) [10], particularly in cases where the concept of automation adaptation [11] is, or can be, adopted. Regarding work on such human-centered manufacturing spaces, Li et al. [12] designed a semantic model of Manufacturing Tasks, capable of providing a plausible manufacturing resource recommendation framework, mainly concerning manufacturing resources, such as processing equipment, materials, labour force, and so on. Its goal is to enable production planning simulation and optimization in a digital twin shop floor. Similarly, in [13], a recommendation system model is proposed using Reinforcement Learning (RL) approaches and trust models, to improve the decision support associated with the execution of the digital twin based on a "what-if" simulation. A Software-Defined Control approach was proposed in [14], to integrate control and enterprise data so as to give a master controller an overview of the entire system and allow her/him to aid operations management solutions with global data and reconfiguration recommendations, that can be rolled out quickly on the shop floor. Bachinger et al. [15] concentrate on the control of predictive models used in smart manufacturing settings, that combine numerous heterogeneous models to generate a digital twin of the production process.

Creutznacher et al. [16] introduce a conceptual planning and optimization framework that compares capacitative production planning adaptations to alter production volumes. The recommendation system for supporting simulation-based production planning selects appropriate variations from a data set and compares them using user- and scenario-based weighting. To create a self-learning system, it is sufficient to run the desired option, and then send the collected Key Performance Indicators (KPIs) back to the database for further analysis. Romeo et al. [17] suggest a data-driven design support system to aid with corporate design. ML predicts machine data and metrics based on manufacturer specs. Decision/Regression Tree, Nearest Neighbours, and Neighbourhood Component Features Selection extract decisional information from heterogeneous data. Designers and experts use the estimated factors to make the best technological conclusion. Thanks to non-technical features (such as cost and market), the tool may be used to assess project feasibility, make offers, etc.

Chen & Jin [18] suggest ranking and selecting the optimal compute pipelines for a given environment, structuring the topic as a recommendation problem. Their system takes into account similarities across computation pipelines, based on word embedding and context characteristics, effectively discovering the highest-ranking ones without exhaustively experimenting with all pipelines.

3 METHODOLOGY

This section presents the developed DNN architecture model, and describes the case study elected to validate it, provided by an elevator manufacturing company.

3.1 Case study description

Our selected use case was implemented with assistance from an elevator manufacturing company. The production of customer-tailored hydraulic lift solutions entails production processes that need to meet the highest of standards, to ensure safety and quality of the final product delivered to the customer. Therefore, quality testing is an inseparable part of every manufacturing step. However, as client demands and requirements vary, so does the product's Bill of Materials (BoM), and therefore, test requirements and conditions, change.

One of the most important components in elevator manufacturing is the hydraulic press unit, which is key for ensuring proper operation in accordance to the customer's specifications. Therefore, quality testing of this unit occurs at a dedicated test lab, where operational conditions are simulated to identify defects. Such defects may involve faulty components in the unit's build, or improper calibration, which may impact the elevator's operation in terms of lift speed, vibrations, and sound. Because of the highly customised production, quality control is carried out manually by PLOs, which is both a time-consuming and error-prone process.

We thus developed a RS to address the needs of hydraulic press unit calibration, in order to reduce the number of manual inspections needed for different configurations of the lifting mechanism. The system is based on a DNN architecture, utilising collaborative filtering and factorization matrix approaches, and is trained on a dataset provided by the manufacturer, capable of predicting speed and pressure calibration values for the hydraulic block valve. These pre-determine the velocity and acceleration of an elevator that are described by the specific BoM, in order for the elevator to operate efficiently, while also not exceeding the noise level specified by the customer. In this way, the system produces recommendations for a PLO in the test lab, to both recommend the operators with predictions regarding target parameters during the hydraulic press calibration task. Next sections describe the dataset, along with the pre-processing carried out for training the RL agent to yield predictions for speed and pressure calibration values for a specific BoM of an elevator mechanism.

3.2 Dataset

The dataset comprises unit test results carried out by the elevator manufacturer over a period of two years. It includes a time series regarding the benchmarking of hydraulic valves in terms of velocity (speed), oil pressure and noise for 7.200 different elevator configurations over these two years. Each configuration consists of the parameters summarized in Table 1.

Table 1: Elevator configuration (Bill of Materials)

Parameter	Description
ORDER	A unique number corresponds to a specific client's order for a specific elevator configuration that needs to be constructed.
HAND PUMP	The type of hand pump that is used for the calibration of the elevator.
FLOW RATE	The oil flow rate for filling up or out the hydraulic press pistons so as to lift up or down the elevator accordingly.
PRESSURE SWITCH	The type of pressure switch that is used as an electric latch for starting or stopping the oil flow from the oil tank to the hydraulic valve and vice versa.
PISTON SNO	A unique numeric identifier (serial number) of the hydraulic valve piston used for the specific configuration.
POWER UNIT SNO	A unique numeric identifier (serial number) of the power unit used for the specific configuration.
TANK TYPE	The type of hydraulic oil tank that is used for storing the oil for the specific configuration.
BLOCK VALVE	The type of block valve which is used for regulating the speed and pressure of the hydraulic press for the specific configuration.

Each configuration ensembles the lifting mechanism of an elevator that is built by the manufacturer for a specific client's order. This mechanism should be calibrated for operating in a specific spectrum of speed values, and it should not produce noise above a specific threshold, which depends on the legislation in each country. Testing of the elevator mechanism is conducted during the unit testing procedure, through which the operator can observe the behaviour in the lab, gauging mainly three parameters: speed, pressure, and noise. Each unit test provides time series data similar to those depicted in Figure 1.

Specifically, the speed results are measured in meters per second (m/s), the pressure in bars and noise in decibels (dBs).

The dataset contains valid unit test results for each of the 7.200 different configurations. For example, the configuration that pertains to the unit test measurements of Figure 1, should operate so that the mean speed is at 0,19 m/s, the average oil pressure is at 35 bars, and the noise produced does not exceed 70 dBs.

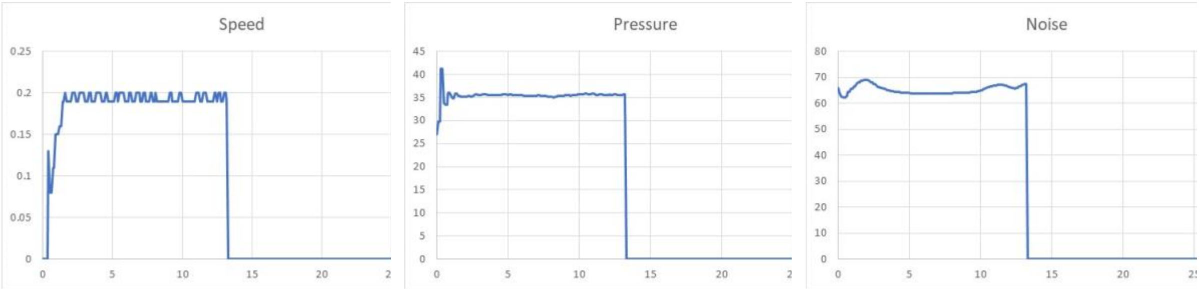

Figure 1: Example unit test results of a specific configuration

3.3 Dataset exploration and pre-processing

RSs are intended to support workers in optimal decision-making, essentially augmenting their capability to identify the optimal choice out of a number of available options. Likewise, the main objective of the implemented RS is to assist the test lab PLOs during the calibration phase, adjusting the block valve so as to achieve the optimal values of mean speed, pressure, and noise. To that end, the proposed mechanism should consider the configuration parameters, as described in Table 1, and the target values for the aforementioned characteristics.

As can be observed in the measurements illustrated in Figure 1, the time series for each characteristic (speed, pressure, and noise) follows a specific pattern, which corresponds to the mechanical characteristics of an elevator. In detail, regarding the speed characteristic, there is an acceleration phase for the elevator speed (either going up or down) during which the values continuously increase. Related to pressure, a ramp-up phase is observed, during which the pressure has high values. After this initial phase, we can observe that there is an equilibrium for both characteristics, fluctuating within a niche range of values, slightly higher, or lower than the target one. Regarding noise values, an initial fluctuation is observed, which is slightly above the mean values, without however exceeding the upper limit.

Considering these observations, we proceeded with the necessary dataset pre-processing, before we fed it to the proposed DNN model for training, as described below.

As per our observations, we decided that the initial phase of the unit test results should be trimmed both for speed and pressure. This is because our overall objective is to produce a dataset that will provide values near the target one, thus all the values of the initial phases are considered outliers. To that end, for each individual unit test, we cut off all the values included within the initialization phase, as well as any zero values. The remaining values pertained to the equilibrium phase, so they could be used to find the average speed, pressure, and noise values for each configuration, which would constitute the true values for our DNN model. However, if we averaged the remaining values of each configuration, we would considerably reduce the size of the dataset (i.e., to only 7 thousand rows). This would not be adequate for training the model. In this respect, we proceeded with the augmentation of the dataset, by keeping a portion of the remaining values, as described next.

Having ensured that the data pruning procedure yielded a dataset including values only from the equilibrium phase of each unit test, we decided to keep a wide range of these values, rather than averaging them to one single value. To do so, we first proceeded to finding local maxima and local minima of the equilibrium phases, exploiting the fact that, in this phase, the values of the data stream fluctuate. Hence, we were able to define existing plateaus and valleys. An example is illustrated in Figure 2.

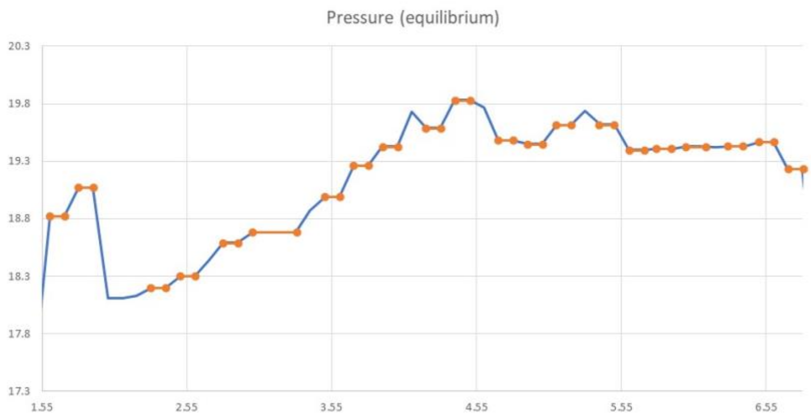

Figure 2: An example of the oil pressure values, at the equilibrium phase, for a configuration. The orange annotated segments designate the plateaus and valleys that have been identified by local maxima or minima, respectively.

Having aggregated and averaging the identified plateaus and valleys for each configuration, we then calculated their average value, which is close to the desired target (mean) values, as well as their standard deviation. For the final dataset we kept only the values falling within the range of:

$$average\ value \pm standard\ devation \tag{1}$$

As a last step before proceeding with the training and validation of our model, we carried out (min-max) normalization of the pressure oil values, succeeding this way the acceleration of the training process without affecting the actual distribution of these dataset features.

4 CASE-BASED ANALYSIS & RECOMMENDATION

Considering that the main objective of the RS is to predict target values for specific configurations (so that the operators can try fine-tuning the block valve without needing to proceed to unnecessary unit tests), we propose a DNN architecture inspired by the collaborative filtering and factorization matrix approaches based on DNNs, like those described in section 2.

In traditional ML approaches, the features are manually engineered by field experts. On the other hand, provided that a regression task is compositional, and the dataset size is sufficient, DNNs have the ability to automatically learn useful features from the data. Furthermore, in many cases, these features outperform handcrafted ones, leading to improved classification accuracy. Hence, combining the characteristics of the aforementioned approaches we concluded to the DNN architecture illustrated in Figure 3.

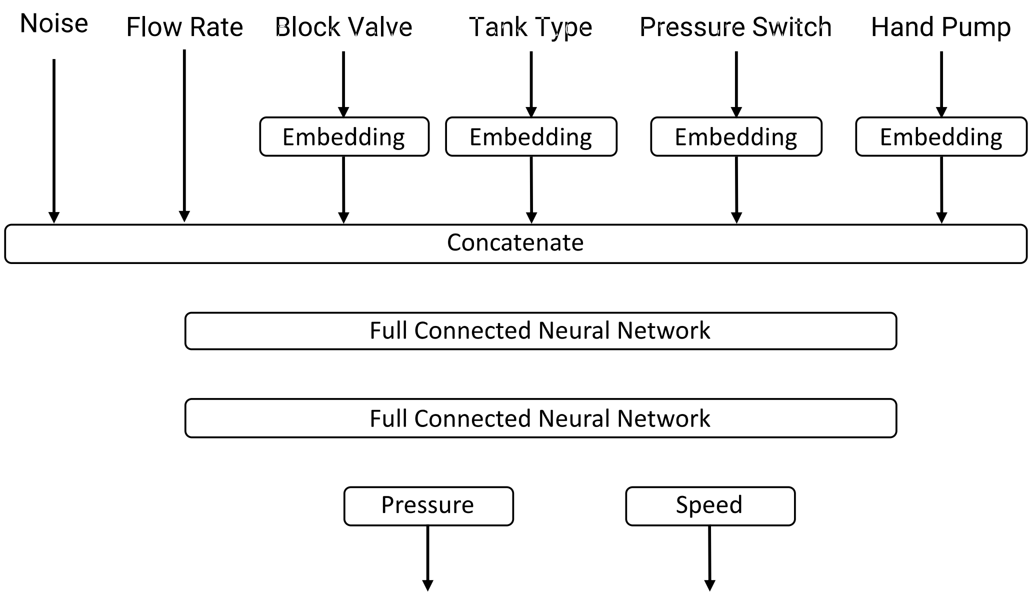

Figure 3: The proposed ML architecture for our recommender system

Specifically, the proposed ML architecture takes as input the configuration parameters (as described in Table 1), as well as the target noise value. It consists of four embedding layers, which are used for indexing each of the parameters that specify configuration component types (i.e., the HAND PUMP model; the PRESSURE SWITCH type; the TANK type; and the BLOCK VALVE) into fixed length vectors of defined size. As can be seen, ORDER, PISTON SNO and POWER UNIT SNO are not used in the proposed model, since they are unique for each configuration, without providing qualitative characteristics that could be considered as features for our model.

The embedding layers along with the configuration's Flow rate and Noise, which are used as numeric values, are then concatenated into a single layer. This layer is then sequentially connected to two Fully Connected Neural Network (NN) layers, each one activated by the leaky RELU activation function. The second Fully Connected NN layer is jointly connected to two different Fully Connected NN layers of output size one, which provide the inferred target speed and pressure values.

5 RESULTS

Our model was trained and evaluated on the pre-processed dataset. To identify the best configuration for each task, we tuned our hyperparameters using 10-fold cross-validation. Then, we evaluated the models, trained using the best hyperparameters, on the test set. The train-validation-test split of the data was 60% for the train set; 20% for the validation set; and 20% for the test set.

Overall, the results show that the model performs well, providing an average Mean Squared Error of 0,0015 for the speed, and 0,0078 for the pressure predictions respectively (the validation dataset was not included in the training process to avoid overfitting biases).

Furthermore, the average loss for the predicted values (on the test dataset) was 0,023 for speed and 0,065 for pressure. Table 2 summarizes the loss values for speed and pressure predictions for all the validation runs.

Table 2: Mean loss for speed and pressure of all the validation runs

Run	Speed loss	Pressure loss
1	0,0226	0,0659
2	0,0238	0,0651
3	0,0231	0,0642
4	0,0217	0,0663
5	0,0234	0,0638
6	0,0213	0,0654
7	0,0235	0,0653
8	0,0229	0,0648
9	0,0220	0,0650
10	0,0232	0,0640

Furthermore, to investigate the correlation between the dataset label features and the predicted values, we calculated the Pearson Correlation Coefficients (PCC) for all the validation runs. PCC quantifies the strength of the linear relationship between the predicted values in adherence with the respective labels. Table 3 summarizes the PCCs of speed and pressure for all the validation runs. It can be observed that, despite the different datasets used for the model training – test – validation, all the values for both prediction variables were stable, with almost zero standard deviation.

Table 3: Mean loss for speed and pressure of all the validation runs

Run	Speed PCC	Pressure PCC
1	0,969	0,722
2	0,969	0,728
3	0,968	0,725
4	0,969	0,708
5	0,968	0,729
6	0,970	0,715
7	0,970	0,726
8	0,972	0,723
9	0,968	0,714
10	0,971	0,723

As can be observed from the PCC, the speed predictions are very strongly correlated to the corresponding labels, while the pressure predictions present lower coherency. However, it is worth mentioning that both results yield strong associations [19].

Figure 4 presents two scatter plots of the predicted values versus the dataset's true values for speed (at the left) and pressure (at the right). As can be observed, both prediction variables do not present heteroscedasticity, and mimic the true values adequately.

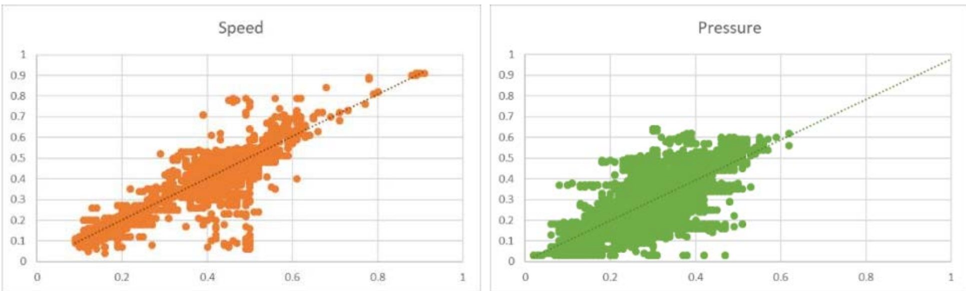

Figure 4: Left: Speed predicted values vs the pertaining dataset features. Right: Pressure predicted values vs the corresponding dataset features.

6 CONCLUSIONS

RSs are intended to support workers in optimal decision-making, essentially augmenting their capability to identify the optimal choice out of a number of available options. Likewise, the main objective of the implemented RS is to assist the test lab PLOs during the calibration phase, adjusting the block valve so as to achieve the optimal values of mean speed, pressure, and noise. Solutions, such as the one described in this work, require tasks where the Level of Automation [21] is sufficiently low, for human PLOs to be at the centre of the operation, and as such, in charge of the decision-making process. To this end, we presented an RS for the configuration of an elevator hydraulic press during manufacturing, which is mainly a manual process that provides a user-focused and data-informed proof-of-concept environment for our solution.

This work thus reports on an ML model for predicting the speed and pressure values of a given dataset. The model was tested on a different dataset to prevent overfitting biases, then trained and evaluated on a pre-processed dataset using 10-fold cross-validation. The outcomes demonstrate the effectiveness of our approach, with average Mean Squared Errors for the speed and pressure forecasts of 0,0015 and 0,0078, respectively. Strong linear correlations between the projected values and their corresponding labels were further highlighted by the Pearson Correlation Coefficient study.

Future work should concentrate on enhancing the model's capability to forecast pressure values. According to our findings, correlation between the anticipated pressure values and their corresponding labels was not as strong as in the case of speed prediction. To enhance the model's capability for pressure prediction, we advise looking at alternative models or data pre-processing methods. Additionally, adding extra characteristics, like the time of day, or the weather, could help the algorithm forecast the pressure levels more precisely. In addition, in order to fully realize a system that can be trusted enough by PLOs to reduce the number of unnecessary tests in real manufacturing conditions, additional long-term AI accountability considerations should be integrated into the solution's design, such as the use of Blockchain for storing the RS prediction results in an immutable manner [22].

Whilst our model was validated for the particular use case, we purport it to be a valuable tool for different applications, such as traffic management systems and driverless cars, due to its high degree of accuracy in speed prediction. Extending the approach for such use cases is left as motivation for future work.

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