Implementing sharing platform based on ontology using a sequential recommender system

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ABSTRACT

While recommender systems have shown success in many fields, accurate recommendations in industrial settings remain challenging. In maintenance, existing techniques often struggle with the "cold start" problem and fail to consider differences in the target population's characteristics. To address this, additional user information can be incorporated into the recommendation process. This paper proposes a recommender system for recommending repair actions to technicians based on an ontology (knowledge base) and a sequential model. The approach utilizes two ontologies, one representing failure knowledge and the other representing asset attributes. The proposed method involves two steps: i) calculating score similarity based on ontology domain knowledge to make predictions for targeted failures and ii) generating Top-N repair actions through collaborative filtering recommendations for targeted failures. An additional module was implemented to evaluate the recommender system, and results showed improved performance.

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1. INTRODUCTION

Contemporary economic developments marked by globalization and digitalization confirm the importance and role of knowledge, in generating innovations, maintaining a competitive advantage in an organization, and continuously adapting to a changing market [1]. This makes knowledge sharing and uses a key research topic within the knowledge management community [2]. Technology has played a key role in this transition and has revolutionized the way organizations manage their knowledge. However, organizations have always struggled to integrate it into their processes [3]. Naturally, the transfer of explicit knowledge is simpler [4]. On the other hand, tacit knowledge whose first source is an experience [5] and is generally difficult to share [4]. In this sense, in previous work [6] we have proposed a complete process based on the socialization, externalization, combination, and internalization (SECI) method for the optimal collection of explicit and tacit knowledge from each technician [7]. This knowledge base has been formalized by two ontologies, the 1st for rolling stock and the 2nd for failures. This sharing of knowledge via ontology allows each system to exploit all the knowledge of the other systems [8]. Moreover, the recommendation system, which can be applied to the ontology, brings a benefit to this knowledge while being able to generate new knowledge that the users cannot notice [9]. An ontology-based recommendation system is a type of recommendation system that uses an ontology to represent and organize the domain of items being recommended [10], [11]. An ontology is a formal representation of a set of concepts within a domain, and the relationships between those concepts [12]. Using an ontology in a recommendation system can help to improve the accuracy and relevance of recommendations by allowing the system to reason about the relationships between different items and users [10], [13], [14]. Regardless of the approach used to build the ontology, an ontology-based recommendation system typically involves the use of natural language processing (NLP) techniques to extract information from the ontology and use it to generate recommendations [14], [15]. This may involve identifying relevant concepts and relationships in the ontology and using them to find items that are likely to be of interest to a particular user [16]. Knowledge transfer is a powerful lever for growth and an essential device for consolidating all of a company's knowledge [17]. Based on this process, the company can generate several benefits including [18]: increased efficiency and productivity leading to increased revenue, leader development across the organization, and improvement in adaptability across individual teams and the organization as a whole.

Recommender systems are types of expert systems [19], that are used to make recommendations about products, information, or services to users. Most existing recommender systems implicitly assume a particular type of user behavior. However, they rarely consider interactive user recommendation scenarios in real environments. In this paper, we propose to implement a sharing platform for railway maintenance based on an ontology and using a sequential recommender system, following the steps shown in Figure 1.

Figure 1. The stages of construction

By following these steps, we can build a sharing platform for railway maintenance that leverages the power of an ontology and a sequential recommender system to provide personalized recommendations to users. The following sections of the document are presented as follows: section 2 presents the proposed method and the case study; then section 3 presents some related work, and finally an evaluation of the system and conclusion in the last section.

2. THE PROPOSED METHOD

2.1. Motivation

In the continuity of our work, we propose in this article to redefine the current role of knowledge as well as its dynamics of creation and its management mechanisms by bringing out new perspectives on this knowledge. From this perspective, maintenance assistant for rolling stock (MARS) was developed. MARS is a recommender system that allows the exploitation and sharing of knowledge, in a framework of continuous learning between the different technicians of the railway company. MARS will provide personalized and automated maintenance recommendations based on historical data, past maintenance records, and current operational conditions. This will help improve the efficiency and effectiveness of maintenance operations, reduce maintenance costs, minimize equipment downtime, and enhance overall train performance and reliability. By using MARS, maintenance can be proactive, data-driven, and optimized to prevent equipment failures and prolong its lifespan.

2.2. Description

The functionality of MARS consists of proposing the most suitable repair actions to remedy the failures of rolling stock on a rail network. The system will allow the collection of information and the application of actions according to the typology of the incidents with the objectives of reducing the time of immobilization and repair on the one hand and reducing the quantity of these in the future. MARS will make it possible to consult the workflow at any time, record feedback from the experience, and disseminate the information that the company wishes to take into account in the capitalization process on rolling stock failures. MARS will have its origin in incidents reported to technicians. These incidents will have their own independent life cycle but are interconnected with the repair life cycle through this system. The interconnection of incidents with MARS is carried out using middleware for extract-transform-load (ETL). The ETL batch process will be periodically configurable (time interval, in days) which will get rolling stock incidents.

2.3. Approach and functionalities

MARS process will go through the following different stages detailed in Figure 2, to facilitate the repair process for rolling technicians, the system must guide them through all the necessary steps. To achieve this, the system needs to be able to open an action sheet. The first step in this process is to analyze the predictions. To do this, a time-series and neural network (NN) approach has been set up to predict failures, classify them, and evaluate their impact on traffic [20].

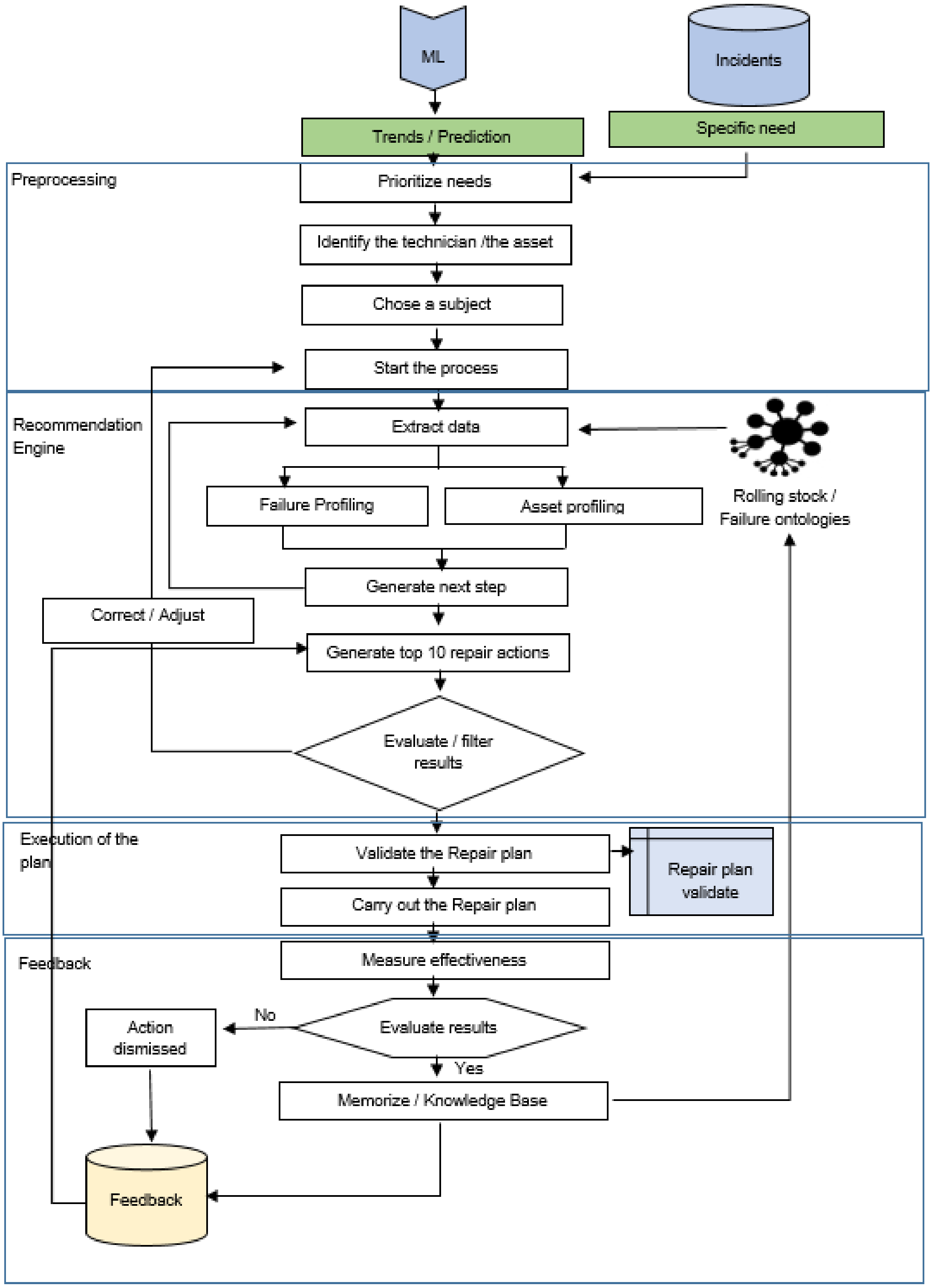

Figure 2. MARS workflow

These failures will be recovered using a batch process and integrated into the recommendation system. However, the evaluation process for predicted failures will differ from actual failures. If the recommended action plan successfully prevents a predicted failure, it will be considered useful for future reference. On the other hand, if it does not prevent the predicted failure, the plan will be considered ineffective. The system also needs to address specific needs, such as incidents reported in the event management system (EMS) that require intervention. These incidents will be individually retrieved through a daily batch process and added to the incident list. Regardless of the origin of the failures, each will follow the same flow through the recommendation process, from input to output. A search engine will be set up to filter the failures likely to be processed, according to the criteria as the type, class, and location.

2.4. Recommendation engine

The recommendation process is a crucial stage that marks the beginning of a project's evaluation. During registration, a recommendation code is assigned to the project, which serves as an identification key for retrieving the project from the search engine of projects. This code ensures that the recommendation project is easily accessible to the concerned parties, who can then assess its viability and make informed decisions. Once the technician and the asset subject to the failure have been identified, the extraction of information from the ontologies commences. This extraction is done based on the fields that have been selected from a predefined list. The fields chosen to depend on the nature of the project and the kind of information that needs to be extracted. The extraction process aims to provide accurate and relevant data that can be used to make informed recommendations. The extraction of information from ontologies is a complex process that requires the use of sophisticated tools and techniques. These tools are designed to extract information from various sources, including databases, expert systems, and knowledge graphs. The information extracted is then analyzed to identify patterns, trends, and relationships that can be used to generate recommendations. The use of ontologies in the extraction process ensures that the information extracted is relevant, consistent, and accurate, thereby enhancing the quality of the recommendations generated. At this point, the recommendation process begins, the screen will contain 5 tabs as shown in Figure 3, which will contain the following information:

Tab 1: The data of the failure to be processed for the beginning of the recommendation process, and the list of failures that correspond to one of the criteria.
Tab 2: The list of symptoms similar to the scope defined in tab 1.
Tab 3: The list of causes similar to the scope defined in tabs 1 and 2.
Tab 4: The top 10 repair actions.
Tab 5: The action plan generated as a result of the section in tab 4.

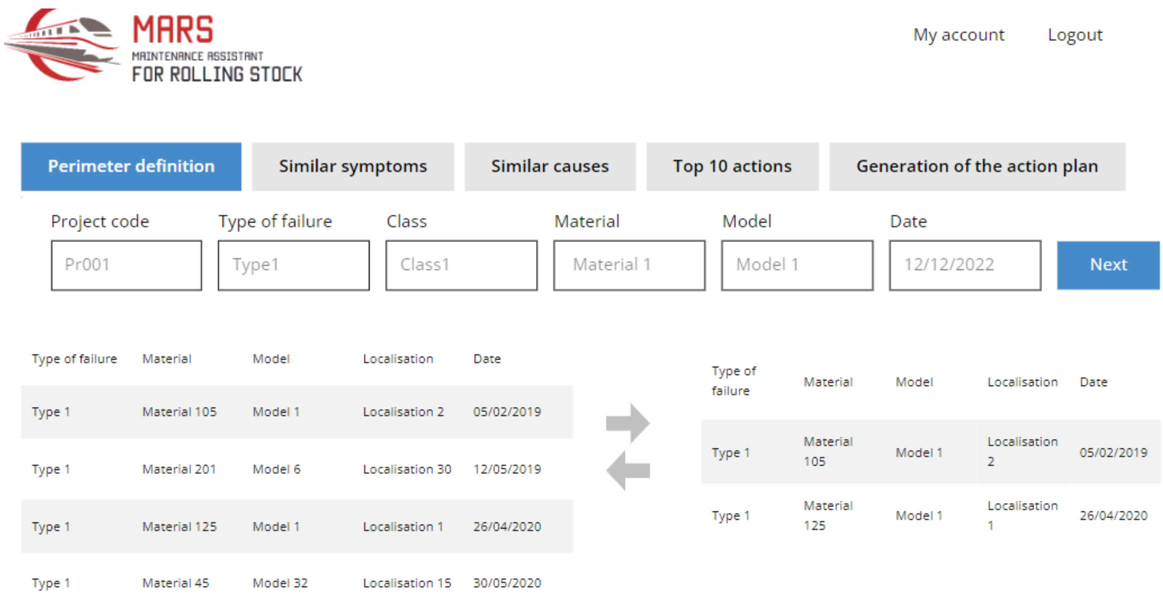

Figure 3. MARS screen of perimeter definition

There are many similarity metrics used in recommendation systems, and one of the most commonly used similarity metrics Is cosine similarity [21]. Based on matrix factorization, this technique decomposes the failure-action adaptation matrix according to the interaction of the technician into a lower-dimensional failure and action feature matrix. The predicted rating for a failure is the dot product of the failure and action feature vectors [22], [23]. The cosine similarity score between two symptom or causes, x and y, is as (1).

$$Cosine\ (x, y)\ = (x * y)\ /(|(|x|)\ | * |(|y|)\ |) \tag{1}$$

The cosine similarity score is calculated as the cosine of the angle between the two vectors, which represents the similarity between the symptoms. A score of 1 indicates that the symptoms are completely similar, while a score of -1 indicates that the symptoms are completely dissimilar. A score of 0 indicates that the symptoms are orthogonal and have no similarity [22]. To calculate the cosine similarity score between two symptoms with five features, class, type, failure, material, and model, you would first represent each symptom as a vector in a 5-dimensional space, with each dimension corresponding to one of the five features. For Cause, we add symptoms as the sixth feature. At this stage, the system will propose the top 10 actions to the technician that best fit his interactions as shown in Figure 4. The system will take into account the frequency of use and rating [24]. The rating is calculated based on technician feedback for each action.

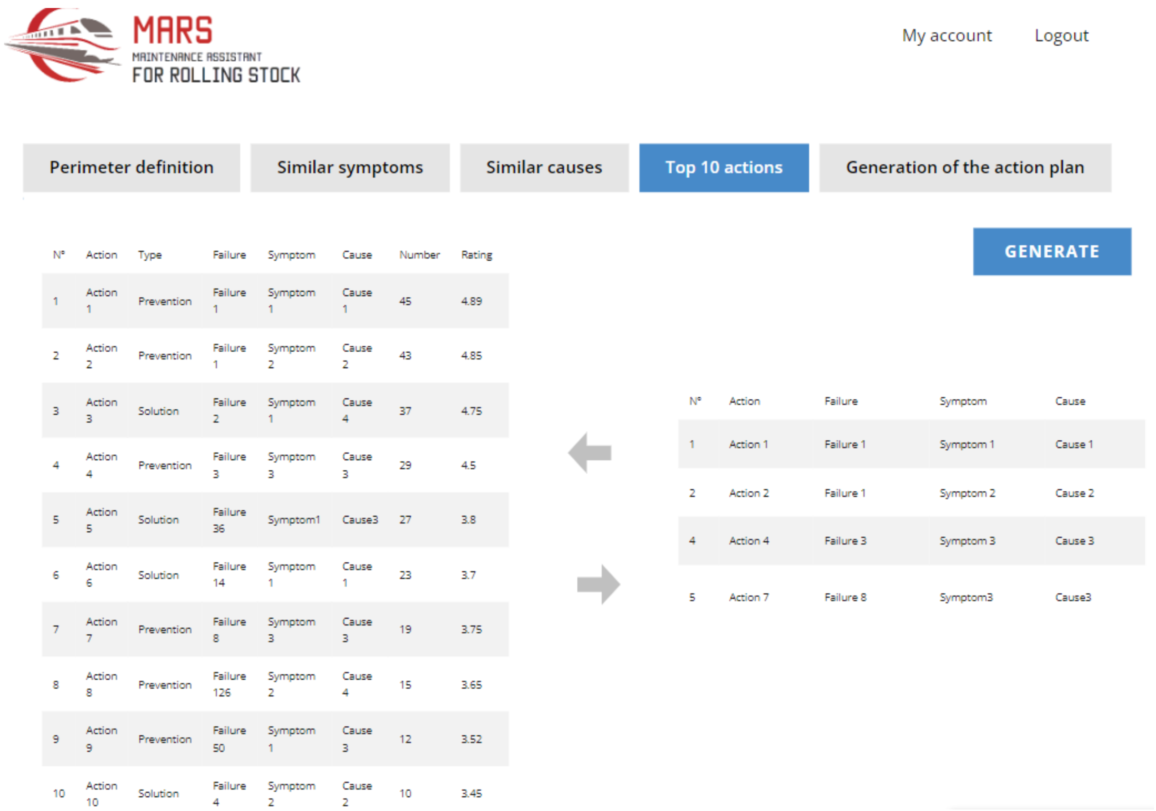

Figure 4. MARS screen of top 10 actions

After validating the action plan, it must be executed. It will be possible to print the selected action plan proposed by MARS. The execution of the plan will be done by the technician after the validation of the expert. Taking into account the case to be treated: a prediction or a specific failure. The objective will be either to avoid failure or correct the failure. This part of the workflow will be realized outside MARS.

2.5. Feedback

The technician will give his evaluation, which must be validated or completed by the expert. If it is a prediction, the success of the action plan is to avoid failure. An additional study can be conducted by the expert to verify the existence or not of regression on other components or the appearance of other failures related to this intervention. For the other case, if it is a punctual failure, the expert has the possibility to define a duration of evaluation, to allow the follow-up of the material and the impact of the action on its functioning before judging its effectiveness. After the technician fills in his evaluation, the expert will have to validate them to trigger the update of the ontology. The update script takes into account only the evaluated and validated actions.

If, after a period of inactivity of a repair plan, the system must put it in the "Unfunded" state, in order to highlight this situation of inactivity. To do this, a batch process is defined, which will check daily the recommended repair plans, whose feedback has not been given and for which the defined period of inactivity has elapsed. This period of inactivity will be configurable and will be defined in the catalog management system.

3. RESEARCH METHOD

There are various studies related to personalized recommendations. Streams are designed to improve the accuracy of algorithms used in recommender systems. The second stream focuses on the interaction between the recommender system and its users. In addition, some studies focus on the influence of moderating factors, such as user characteristics and product characteristics, on recommendation performance.

Das [25] were carried out within the framework of competition 1 of the prognostics and health management (PHM) Society Conference Data Challenge 2013 closely related to remote monitoring and diagnosis in industrial applications. The goal of this data contest is to create an automated system capable of recommending particular maintenance actions to mitigate failures. In response to these failures, domain experts recommend maintenance actions based on the types of issues. Also, they describe the design of maintenance and operational recommenders. Recommenders use information from energy management and control systems (EMCS) and computerized maintenance management systems (CMMS) to recommend what maintenance personnel should do in response to maintenance service requests. It compares the predicted similarity with the similarity calculated by comparing maintenance operations. Ontology reasoning has been shown to improve user personas; external ontology knowledge is used to successfully bootstrap recommender systems, and persona visualization is used to improve personas accuracy [26]. Tashmetov *et al.* [27] determine the malfunction of a specific node or circuit and give advice by an intelligent expert system to troubleshoot the malfunction in railway transport. A mathematical model and an algorithm have been developed, and a program for finding a solution to a malfunction for its elimination in the circuits of two-wire arrows has been compiled.

However, the results demonstrate that ontology-based approaches can achieve interoperability of heterogeneous knowledge representations and lead to accurate recommendations. The use of these methods in practical recommender systems demonstrates the applicability of the results to real environments [14], [28]. Therefore, in a recommendation, Tarus *et al.* [29] use ontologies to model and represent domain knowledge about learners and learning resources. Evaluation of the proposed hybrid recommender system shows improved performance. In the field of maintenance, we have identified a few articles that focus on the use of knowledge-based recommender systems in the maintenance domain. Al-Najim *et al.* [30] used previous maintenance reports, which included the status of errors and maintenance actions actually performed in the past, to assess the accuracy of recommendations. They concluded that the hierarchical recommender system, where the system starts by estimating one of the maintenance attributes, which is used as input for estimating the next maintenance attribute in the next step outperformed the single-tier system, which is based on a one-level recommendation of error messages and descriptions in terms of accuracy. And that the multi-tier system may help maintenance teams respond to unexpected equipment failures by operating on the maintenance staff's recommendations. In the same context, Huang *et al.* [31] design a decision support system capable of combining prior knowledge and the past experience of experts to provide personalized maintenance documents. Different maintenance activities are recommended for different users by taking into account different typical utilization conditions of each product instance. Jongwook [32] proposed an ontology-based recommender system to support the maintenance of Korean architectural heritage. They have designed the ontology which expresses the information of the cultural heritage of Korean wooden buildings with reference to existing heritage ontologies. Second, they have created the repair information database based on repair content and expert interview data. Third, they have developed a system that recommends the repair method of Korean wooden architectural heritage with the most similar phenomena and causes.

From the literature reviews described above, there is little research that focuses on maintenance in rail transport while using ontologies. In addition, rare are the systems that provide personalized maintenance documents for each case according to their characteristics, and circumstances. The additional advantage that we have put in our system is the evaluation module that will allow technicians to evaluate the action plans recommended by the system. This data will be integrated into the workflows and will further improve the system's recommendations. Most ontologies available today were created by domain experts to meet certain domain requirements and remained static unless a change within the ontology was made by an individual [32], [33]. However, in our evolution phase, a script was added at the end of the process to evolve our ontology and ensure complete and correct semantics. Maintenance in general remains a very resistant activity in the face of change and presents several constraints considering the companies, namely the age of the assets, change of the assets and their characteristics; the departure of the experts leaving the companies to face daily challenges to ensure this key performance indicator (KPI). The mean time to repair (MTTR) time to repair remains among the most critical indicators that need to be reduced [34]. Hence the essential added value of our project will be an additional and essential aid to technicians in their daily lives.

4. RESULTS AND DISCUSSION

MARS has set two major objectives which are to optimize repair time (MTTR) and minimize the number of failures. In order to evaluate the system's effectiveness, the indicators reported from the field will be taken into consideration. The evaluation process is divided into two levels. The first level is performed by the technician who will assess the recommended repair actions. The second level of evaluation involves measuring the impact of using the system on business indicators, namely MTTR and the number of failures in the long term. These evaluations are crucial to ensure that MARS is meeting its goals and providing the best possible service.

4.1. Evaluation of MTTR

To make it happen, we built on previous work [34], in which we compared a set of regression algorithms to predict MTTR. The results obtained showed that linear, polynomial, and Lasso outperform other algorithms. In this phase of our work, we are going to analyze the duration of the interventions during one month, after the use of MARS, for the same type of failure treated in [34]. We got the result presented in Table 1.

Table 1. Average repair time in hours for different types of failure

Type	Type10	Type11	Type12	Type13	Type14	Type15	Type18	Type2
Before	171.21	121.21	169.61	168.5	31.67	99.72	140.66	102.33
After	171.13	120.05	163.31	167	33.60	100.2	110	99.1

In order to analyze the effectiveness of the three regression algorithms-linear, polynomial, and Lasso in predicting the data, the dataset used in a previous study [34] will be updated with new data. The updated dataset will be used to apply the three algorithms and the results for mean squared error (MSE) and R^2 will be recorded. These results will be presented in Table 2 to compare the performance of the regression algorithms before and after the injection of the new data.

Table 2. Results of regression algorithms

	Before [34]		After	
Algorithms	R^2	MSE	R^2	MSE
Linear regression	0.9965	0.0001	0.9975	0.0001
Polynomial Regression	0.9965	0.0001	0.9968	0.0001
Lasso Regression	0.9961	0.0002	0.9962	0.0002

The results show a slight improvement with the use of MARS, which indicates promising potential for future applications. To further evaluate the effectiveness of MARS, future testing could involve inexperienced recruits, rather than trained and experienced technicians, to determine its performance under different circumstances. This could provide more significant results and insights into the system's capabilities.

4.2. Evaluation of number of failures

For the evaluation of MARS, we continued our work with the pilot site, which provided us with the additional elements necessary for this stage. Indeed, we have recovered the history of breakdowns over the last two years, for reasons of confidentiality, all the data has been treated in a confidentiality framework like the rest of our work. The data retrieved includes the type of incident, the nature of the incident, the date, the place, the material, and the severity. The results of our previous work where we predicted the number of failures per day for each material [20], indicate that the support vector regression (SVR) model with a gamma value equal to 0.03, allows for obtaining satisfactory results with an root mean square error (RMSE) equal to 0.879. After the application of the SVR on the dataset of our pilot site, we applied the model for two consecutive months before and after the use of MARS. To be able to measure the effectiveness and impact of MARS on our prediction model, we calculated the RMSE. The results of our experiment are described in Table 3.

The SVR once again proves its effectiveness on this new dataset with an RMSE equal to 0.8563 on M-1. After the launch of MARS on the site, the workshop managers and unit managers treated 30.77% of the predicted incidents on average over the month M. Even if the figure remains low in some way, but its impact on the number of real breakdowns remains satisfactory and visible. Our previous work has proven the effectiveness of SVR to detect peaks and outliers, this experiment has shown that during the days when we have a peak and the technician has not treated in advance the totality of the breakdowns predicted in MARS, it is these days that have made the difference in the calculation of RMSE of our model, for example, the days: 12 and 24.

Table 3. The results of experiment

Day	Prediction (M-1)	Real (M-1)	Prediction(M)	Prediction(M)	Prediction(M)
1	4	4	3	2	2
2	0	1	1	0	0
3	1	1	1	0	2
4	1	2	2	1	1
5	0	1	1	1	0
6	2	2	2	2	1
7	0	1	2	0	1
8	1	1	3	1	3
9	1	0	1	0	0
10	4	4	1	0	1
11	2	2	0	0	2
12	3	2	6	2	3
13	0	1	2	1	0
14	0	2	2	2	1
15	2	3	1	0	0
16	1	0	3	1	2
17	1	1	3	1	1
18	0	0	5	2	3
19	1	1	1	0	1
20	4	4	0	0	0
21	0	0	2	1	1
22	2	2	0	0	1
23	2	1	1	0	0
24	0	1	6	2	3
25	5	5	3	2	1
26	2	1	1	0	1
27	4	4	0	0	1
28	2	3	1	1	0
29	5	5	3	1	2
30	2	3	0	0	0
	RMSE=0.8563			RMSE=1.354	

4.3. Synthesis

Our first evaluation test discussed in the previous paragraph shows the positive impact of MARS in the reduction of predicted failures and the improvement of repair time. These results remain promising and encouraging to further generalize the use and exploitation of MARS by the rest. We are aware that the implementation of predictive maintenance is very expensive and complex, but with these first results, we can push further the work and try to integrate the preventive maintenance programs to propose action plans combining the two and then minimize the cost of predictive by integrating the cost of preventive. Among the very interesting comments that came back from the technicians, one of them confirmed that the system succeeded in proposing a plan, even if the incident is not in the knowledge base, by using the recommendation techniques used by MARS to alleviate the problems of cold start and sparse data by exploiting the knowledge of the technicians on similar cases before the initial data is available [35].

5. CONCLUSION

In this paper, the study has progressed to the stage of evaluating and recording feedback on proposed repair plans and the steps of integrating the feedback to readjust the recommendations as well as updating the ontologies. The implementation of MARS is one more step towards Maintenance 4.0. The implementation of MARS and before the construction of the ontology was the solutions decided by the top management to face a huge departure of experts and a loss of important knowledge and know-how. In addition to its role of providing intelligent assistance to technicians in their daily work, MARS will allow the conservation and sharing of knowledge between different technicians. The integration of an expert profile in the validation of action plans and the evaluation of plans will ensure the consistency and quality of the recorded data. In addition, we plan to improve the system by integrating the logistical requirements (spare parts, material means) to improve the recommended repair plans. On the other hand, an awareness and communication campaign are essential to make the technicians more reliable and to motivate them to integrate MARS into their daily work. Another level of improvement is mainly related to the ontology used, indeed our system was based on a prototype of a single maintenance center, the generalization and evolution of the ontology are essential to extend the scope of MARS.

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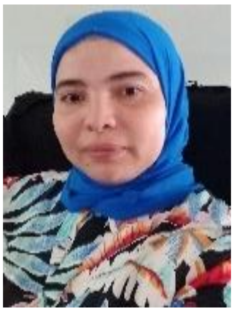

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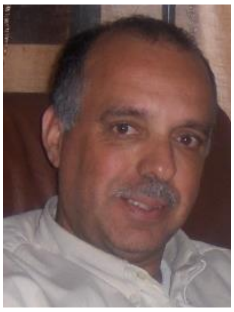

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