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LESSONS LEARNED FROM DEVELOPING AN INDUSTRY 4.0 MOBILE PROCESS MANAGEMENT SYSTEM SUPPORTED BY ARTIFICIAL INTELLIGENCE

WNIOSKI Z ROZWOJU MOBILNEGO SYSTEMU ZARZĄDZANIA PROCESAMI PRZEMYSŁU 4.0 WSPIERANEGO SZTUCZNĄ INTELIGENCJĄ

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Abstract: Research, development and innovation (RDI) projects are undertaken in order to improve existing, or develop new, more efficient products and services. Moreover, the goal of innovation is to produce new knowledge through research, and disseminating it through education and training. In this line of thinking, this paper reports and discusses the lessons learned from the undertaken project, regarding three areas: machine learning (artificial intelligence), computational intelligence, and database management systems (DBMS). As nowadays, a numerous of the RDI projects are oriented towards the development of data-intensive solutions, the authors are confident that these lessons will be valuable not only for data engineers, but also for those researchers and practitioners who are dealing with the issues related to building and validating machine learning models, applications of moving averages to high-frequency data streams, and the implementation and deployment of DBMS.

Keywords: Industry 4.0, mobile, process management, artificial intelligence, research, development and innovation (RDI).

Streszczenie: Projekty w zakresie badań, rozwoju i innowacji (BRI) są podejmowane w celu udoskonalenia istniejących lub opracowania nowych, bardziej wydajnych i skutecznych produktów i usług. Ponadto celem innowacji jest tworzenie nowej wiedzy poprzez badania oraz rozpowszechnianie jej poprzez edukację i szkolenia. W tym duchu rozumowania w niniejszym artykule autorzy przedstawiają i omawiają wnioski wyciągnięte z podjętego projektu, dotyczące trzech dziedzin, a mianowicie: uczenia maszynowego (sztucznej inteligencji), inteligencji obliczeniowej oraz systemów zarządzania bazami danych (DBMS). Biorąc pod uwagę, że obecnie wiele projektów BRI jest zorientowanych na rozwój rozwiązań intensywnie wykorzystujących dane, autorzy są przekonani, że wnioski te będą cenne nie tylko dla inżynierów danych, ale także dla tych badaczy i praktyków, którzy zajmują się zagadnieniami związanymi z budową i walidacją modeli uczenia maszynowego, zastosowaniami średnich ruchomych do strumieni danych o wysokiej częstotliwości oraz implementacją i wdrażaniem systemów zarządzania bazami danych.

Słowa kluczowe: Przemysł 4.0, mobilność, zarządzanie procesami, sztuczna inteligencja.

1. Introduction

Research and Development (R&D) projects are characterised by their complexity and interdependence (Gawin and Marcinkowski, 2020; Liu, Luo, Geng, and Yao, 2021). These projects are the response to the highly competitive market and the demand for innovative products and services (Awan, Muneer, and Abbas, 2013; Falkowski-Gilski and Uhl, 2020). Indeed, a prominent feature of R&D projects is their high degree of innovation (Balli and Sigeze, 2017; Grochowski and Zwierzchowski, 2016). The results of R&D are usually commercialised (Albors-Garrigos and Hervas-Oliver, 2019; Bajdor, Pawełoszek, and Fidlerova, 2021), while the know-how and lessons learnt tend not to be disclosed (Gawlik-Kobylińska et al., 2021; Jasińska-Biliczak and Kowal, 2020; Owoc and Marciniak, 2013).

Yet, considering the latest guidelines and frameworks for research, the development and innovation (RDI) activities (European Commission, 2014), encourage the dissemination of the results through means of publication, teaching or any other contributions allowing other projects to reproduce them. Having said that, this paper aimed to answer this need, and provides a summary of the lessons learnt during the RDI project. These lessons incorporate the technical know-how from the following three areas: machine learning (artificial intelligence), computational intelligence, and database management systems. Thus, this paper contributes to the growing body of modern literature by empirically identifying and analysing the enablers and barriers, that support, or impede implementation, and use selected techniques and technologies.

The rest of the paper is structured as follows. Section 2 presents the project setup, in particular the project goals, scope, and settings. In Section 3, the lessons learnt are introduced and discussed, while Section 4 provides the final remarks.

2. Project setup

The project entitled "An Industry 4.0 Mobile Process Management System Supported by Artificial Intelligence" (hereafter called "the project") was carried out by Meritus Systemy Informatyczne Ltd (the project leader), with its headquarters in Warsaw (Poland), in cooperation with the TV and Radio Research Institute (TRRI, the project partner). The budget was 1.2 million euros, and was conducted between January 2019 and December 2021.

2.1. Project goals and scope

The goal of the project was to develop and implement a cloud-based Industry 4.0 process management information system, facilitated by six AI modules, available for both web-based and mobile users. In particular, the specific project's objective was to design and implement a decision support system (DSS) devoted to improving the user's decision-making capabilities with regard to hazard detection and prediction, as well as recognition of the failure states and complex failures/alert states.

Moreover, the project aimed at developing soft (non-technical) skills, including interpersonal and behavioural skills in the workplace (Ngang, Yie, and Shahid, 2015), which involve little or no interaction with machines. However, soft skills are essential for personal development (Taylor, 2016), effective collaboration and communication (Weichbroth, 2022; Weston, 2020), ultimately contributing to building relations among employees and their work effectiveness (Dogara, Saud, and Kamin, 2020; Wieczorkowski, Chomiak-Orsa, and Pawełoszek, 2022). In this context, the two objectives concerned:

- building the awareness of employees that their actions, directly related to production processes, have a significant impact on their safety;
- building the employees' awareness that their activities, directly connected with production processes, have a significant impact on environment health and safety (EHS) (Thibaud et al., 2018), physical infrastructure, the manufactured products quality, as well as labour costs (direct and indirect), customer relations, and finally, on company revenue.

The scope of the project falls into the smart factory domain, thus following the modern trend of automation and data exchange in manufacturing technologies, including cyber-physical systems (Lee, 2008), cloud (O'Donovan, Gallagher, Leahy, and O'Sullivan, 2019) and cognitive computing (Janus et al., 2021), and the Internet of Things (Bytniewski, Matouk, Rot, Hernes, and Kozina, 2020).

2.2. Project settings

In order to meet the aforementioned goals, the project work breakdown was decomposed into the following seven tasks:

1. Design, development and evaluation of the machine learning models.
2. Design, development and evaluation of the DSS architecture.

3. Machine learning models tuning and optimisation.
4. Machine learning models tuning and optimisation – experimental validation.
5. DSS testing and validation.
6. Assembling the DSS prototype.
7. Deploying and validating the DSS prototype.

The process of developing the concept of the system, and in particular the expectations of artificial intelligence, involves specialists and experts of the Applicant and Partner from the following departments: production, commercialisation and implementation, technological marketing, IT, economic, technical, planning, security and safety, environmental protection, health and safety and fire protection. Their knowledge and experience, given the size of the companies, the scope of their operations and other areas of business, is very useful at the initial stage of concept development, followed by research and testing of the model and prototype solutions.

2.3. System components

At the very start, the DSS was designed as a component-oriented system (Hutchinson and Kotonya, 2005). In total, six components were identified, and generally termed under the umbrella of six keywords: Technology, Environment, Security, Infrastructure, Diagnostics, and Synergy. Below, the authors provide the description and underlying assumptions of the each component.

Technology is understood in terms of the process of detecting potential deviations from the preset electricity consumption curve over a daily period. For each object, and technological area, it is possible to define an energy consumption curve. Deviations from the curve's character can indicate, for example, illegal consumption or the improper configuration of equipment, such as the operation of air-conditioning units at night. The detection of potential deviations from the preset energy consumption curve brings a tangible benefit in optimising energy consumption, and allows the detection of potential energy theft.

Environment is understood in terms of the process of detecting exceedances by the discharged wastewater of the permitted parameters of pH and conductivity (the amount of electric current). The process of industrial wastewater discharge requires close monitoring and an immediate response in situations where the parameters are exceeded. In order to use machine learning for the aforementioned task, a learning and validation dataset representing the allowed space of variation of pH and conductivity parameters of wastewater was developed. The dataset should include at least the following:
- pH value,
- conductivity value,
- information as whether the condition is allowed or not.

Based on the current value of pH and conductivity, the artificial intelligence performs classifications as to whether the set parameters have been exceeded.

Security is understood in terms of the process of detecting the exceedance of the permissible operating temperature range of components. An example area is monitoring the temperature of the busbars connectors in an electrical switchgear. An elevated temperature indicates the degradation of the connection, resulting in a further increase in temperature during operation. Another negative feature is the faster degradation of the component's insulating elements. A consequence of the loss of insulating capacity is, in most cases, the ignition of an electric arc, the fast-moving nature and high energy of which can cause gigantic losses to the infrastructure and, in many cases, ends in death or severe burns to those near the site of such an accident.

The application of machine learning techniques for the aforementioned task requires the development of a synthetic data generator. The generated datasets represent the heating of an electrical power distribution board. Here, it should be noted that the mutual influence of lines on each other was assumed, and therefore the dataset consists of the following attributes:
- the voltage value of the current of line 1,
- the voltage value of the current of line 2,
- the voltage value of the current of line 3,
- the temperature value of line 1 (determined from the model),
- the temperature value of line 2 (determined from the model),
- the value of line temperature 3 (determined from the model),
- the temperature value of line 1 (measured),
- the temperature value of line 2 (measured),
- the temperature value of line 3 (measured),
- 0 or 1 exceeds the allowed temperature, the difference greater than 10 degrees of the theoretical and measured value.

The state of deterioration of the contact was simulated by changing the resistance of the connection, which causes an increase in the power dissipated at the connection and, consequently, an increase in the measured temperature. Moreover, based on the current value of the temperature and the line current, the AI module will be able to infer whether the measured temperature deviates from the theoretical one determined from the model by a value of 10 degrees, if so, it indicates a failure.

Infrastructure is defined as the process of detecting situations of the unauthorized presence of people or objects in an exclusion area. An example of an exclusion area is an area where machines, especially autonomous machines, are operating, and other areas with a high risk of exposing people to death or serious injury.

To feed the machine learning models, the study used geospatial data that combines location information (individual coordinates on the Earth), attribute information (the characteristics of the human object), and also temporal information (the time at which the location and attributes exist). Based on such input data, the classification task is to assign one of the three following classes to the current location of the human object:

- Restricted Zone, an area from which personnel are excluded for reasons of security or safety,
- Warning Zone, an area identified as potentially dangerous,
- Access Zone, an area without limitations to move or work.

The dataset for the learning process in the aforementioned case was created using a synthetic data simulator. The simulator was developed based on a graphical application. The user defines areas using colors, green – safe area, red – excluded area, yellow – potentially dangerous area. Based on the user-defined area, the application generates an array of data for the learning process.

Diagnostics is defined as the process of detecting anomalies in the readings of accelerometer sensors attached to trains. As part of the research work, the authors were able to use real-life data, collected via controlled experiments. A single sensor was attached to one of the trains for at least four hours, enabling data acquisition during its movement and stops.

It should be noted here that it also was necessary to calculate the statistical measures of some attributes in order to distinguish particular states of the train. In particular, four different states was recognized and categorized:
- the train stop,
- the train acceleration,
- the train movement,
- the train deceleration.

Thus, the moving averages approach was adopted, calculated by adding up all the data points during a specific period and dividing the sum by the number of time periods. However, there was a major issue regarding the data inconsistency, since in a period of 1 millisecond the values provided by one sensor could represent two different extremes. To deal with this issue, the high and the low extremes were automatically extracted from the dataset, and eventually analysed separately in the fixed time windows of 10 and 18 seconds length.

Synergy is understood in terms of delivering timely information for the system user, regarding the current operational state of the DSS. Therefore the input data comprises the concurrent and independent data streams from other modules. As part of the research work, a classifier based on a deep-learning approach was prepared, in other words, a classifier based on the artificial neural network was designed and implemented. The feedback provided to the system's user showed the status of the performed data processing tasks, which could bring one of the three possible values: correct, suspected malfunction, and detected malfunction.

3. Lessons learnt

Lesson 1. There was an inclination for developing almost perfect (or perfect) fitted classification models. Hence, the developed models exhibited very high or maximum accuracy (greater than 0.95 or even equal 1.00), and therefore presented

very low error rate or error-free performance, both on the training and test sets (see Table 1 for details). Such results' accuracy and error rates strongly suggest that these models of classifications are far better than mere chance. Nevertheless, in some contexts (e.g. human safety), the cost of making a small number of mistakes, or just one, is still unacceptable.

Table 1. The accuracy of the classification machine learning models obtained for six AI modules

Id	Module	Training set	Testing set
1	Technology	1.000	1.000
2	Environment	0.999	0.995
3	Security	0.990	0.989
4	Infrastructure	1.000	0.992
5	Diagnostics	n/a	n/a
6	Synergy	1.000	1.000

Source: own elaboration.

It should be also noted here that the model's accuracy was calculated as the ratio of the number of cases correctly classified to the total number of input cases (Palimkar, Shaw, and Ghosh, 2022), while the classification models were developed and evaluated by using different machine learning techniques such as: decision trees, artificial neural networks and the k-nearest neighbours (KNN). To divide a single data set into a training set and test set, the study apportioned the data into training and test sets, with an a 75-25 split, while all the classes were represented equally.

However, one obvious question arises now: how would these machine learning models perform on other unseen datasets? First and foremost, the experiments were carried out on self-prepared datasets, based on the settings corresponding to the factual rules and laws which actually govern the particular processes. Nevertheless, such data generators must not be seen as fully reliable since the human bias is unremovable. On the other hand, some very rare cases might be omitted, while others are not able to be defined, and thus computationally generated data samples did not fully cover all possible cases. In other words, the computer simulated processes were not a complete representation of their real-life equivalents.

To sum up, it is extremely important to perform additional experiments on the classifications models using other (external) datasets to ensure their accuracy. By carefully checking and validating the models, one can rely more on the predictions provided.

Lesson 2. There were no overfitted classification models observed. By definition, overfitting occurs when a statistical model fits exactly against its training dataset (IBM, 2021). Consequently, in the case of other (unseen) data, the algorithm will not be able to perform accurately, defeating its ability to generalize. Moreover, an overfitted model tends to demonstrate poor predictive accuracy (Pavlou, Ambler, Seaman, De Iorio, and Omar, 2016).

The issue regarding the overfitting was not recognised, while the accuracy of the developed machine learning models was not significantly different, or even the same, both on the training set and on the test set (see Table 1 for details).

Lesson 3. The moving averages approach provided reasonable signals of anomaly detection. In this case, the time series represented the readings of the accelerometer sensors attached to the train. An anomaly signal was generated when a shorter-term (10-second) moving average crosses above a longer-term (18-second) moving average (see Figure 1 for details).
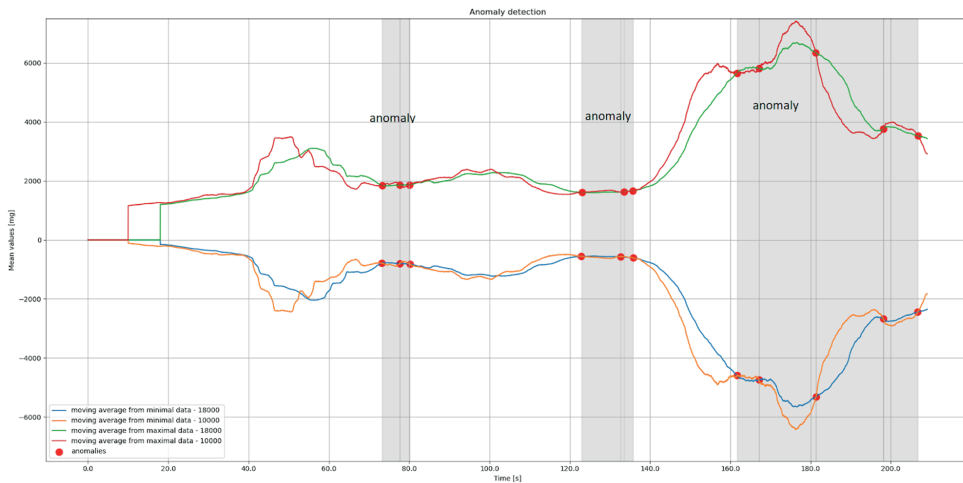

Fig. 1. The view on the sample of a time series and calculated moving averages with corresponding signals indicating the detected anomalies (marked by red points and grey on the timeline)

Source: own elaboration.

In Figure 1, it can be observed that the implemented method detected three fragments of measurements classified as anomalies, the first and second containing three signals of anomalies, and the third five such signals.

Lesson 4. The observed performance of the database management systems (DBMS) was different. Thus, it is not a straightforward task to select an efficient database system from the variety currently available. Therefore, any DBMS implementation and deployment should be preceded by performance benchmarking testing and evaluation experiments, which by design should correspond to the future DBMS settings and workload.

For the record, the experiments involved benchmarking the performance of the two SQL-type database implementation: PostgreSQL 11 and MongoDB 4.0. Both databases were used to archive a large amount of measurement data. The tests were conducted on one physical machine, while the databases were tested sequentially, one by one. The first stage involved a transaction test that simulates a reservation

system, the second a *sysbench* for OLTP (Online Transaction Processing) workloads, and the third a JSON-based OLAP (On-Line Analytical Processing) benchmark test.

The results show that PostgreSQL is several times more efficient than MongoDB. In both cases, performance peaks were reached at 32 threads. Eventually, for both transaction isolation modes PostgreSQL was faster, despite the performance degradation caused by repetitions of transactions in SERIALIZABLE mode.

4. Conclusions

In this article, the four lessons learnt regarding developing and validating machine learning models, adopting moving averages and the performance of the database management systems, were introduced and discussed. The authors are confident that these lessons are easy and valuable to learn, especially for data engineers. Moreover, from the theory's perspective, the results also motivate conducting future investigation of the validity issues related to self-designed and computationally generated datasets. These may open the door for potential weakness and vulnerabilities with regard to the reproducibility of the newly developed machine learning models. In the authors' opinion, the remaining lessons are also useful, by providing insights on the empirically verified application of the moving averages into the problem of train movement anomaly detection, as well as the performance of the two latest versions of the database management systems, available to the public and to use free-of-charge.

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