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ARTIFICIAL INTELLIGENCE IN OPERATIONAL APPLICATIONS OF RAILWAY INFRASTRUCTURE MANAGER

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Abstract. The main goal of this article is to present the possibility of using artificial intelligence in operational application of railway infrastructure manager. Railway 4.0 can be controlled fully digitally – operational applications based on the artificial intelligence can optimize the technology of railway traffic control. Thereafter, a wide range of equipment could be controlled by application through a secure interface.

Keywords: Artificial intelligence, operational applications, railway traffic control, railway 4.0.

1. Introduction

Railway 4.0 should be completely digital. Railway traffic control should use the digitization as much as possible. One rail network (topology) completely connected information systems with secure interface with other devices (safety equipment, ETCS etc.) should not be blank phrases.

The aim of this article is to present the possibility of using artificial intelligence in operational application for optimization the railway traffic control processes.

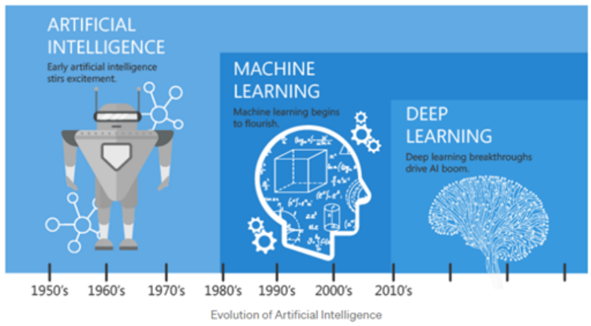

Figure 1. Evolution of AI [1].

2. Materials and Methods

In this article there was used the decomposition of the application to determine the levels of the deep learning. The artificial intelligence topic is quite old (more in the Figure 1), but the implementation in operational apps of railway infrastructure manager is still quite unexplored.

The difference between terms artificial intelligence, machine learning and deep learning is:

- artificial intelligence – a program that can sense, reason, act and adapt,
- machine learning – algorithms whose performance improve as they are exposed to more data over time,
- deep learning – subset of machine learning in which multi-layered neural networks learn form vast amounts of data. More in the Figure 2.

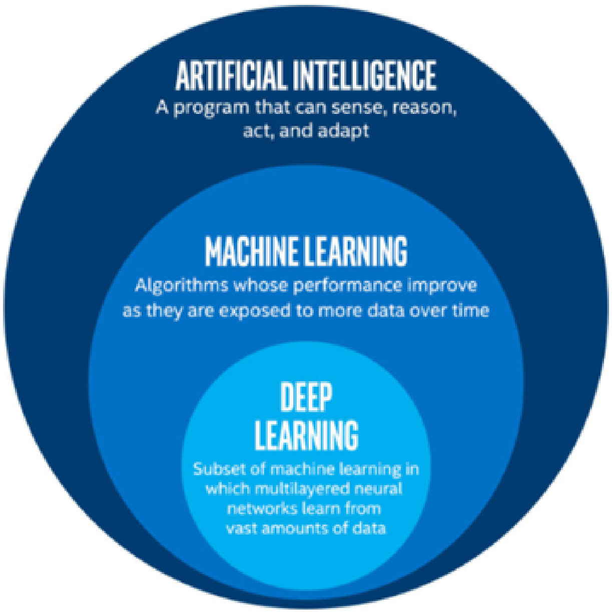

Figure 2. The difference definition [1].

Deep Learning is incredibly young field of artificial intelligence based on artificial neural networks (multi-layered structure of algorithms, more in the Figure 3).

However, the new industrial revolution is driven by artificial neural networks and deep learning – the major advantages are 2: needlessness of the so-called feature extraction and powering by massive amounts of data (big data use).

About feature extraction – the problem is the impossibility of implementation flat algorithms (e.g. decision trees) to the raw data – the step called "feature extraction" must be done. The result of feature extraction is an abstract representation of the given raw data, that you can use for classic machine learning algorithms to perform a task (e.g. the classification

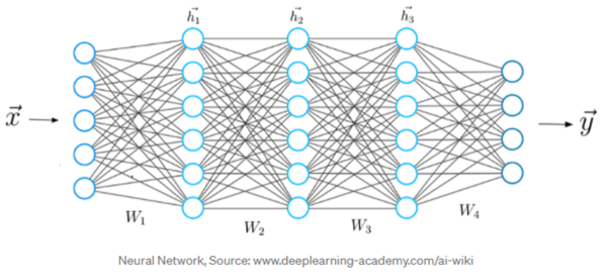

FIGURE 3. Neural network [2].

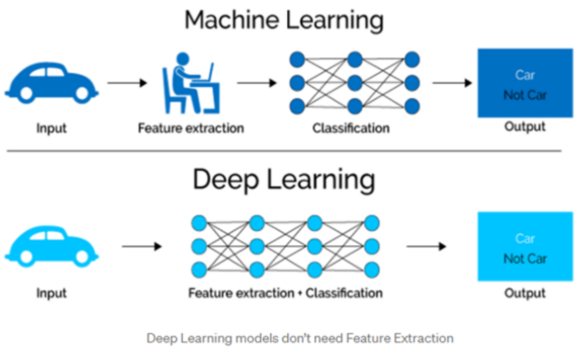

FIGURE 4. Feature Extraction [1].

of the data into several categories or classes). Feature extraction is usually quite complicated and requires detailed knowledge of the problem [3]. This step must be adapted and refined over several iterations for optimal results. And deep learning models don't need it (more in the Figure 4), because the feature extraction step is already a part of the process that takes place in an artificial neural network. During the training process, this step is also optimized by the neural network to obtain the best possible abstract representation of the input data [4]. For example, if you want to use a machine learning model to determine whether a particular image shows a car or not, we humans first need to identify the unique features of a car (shape, size, windows, wheels, etc.), extract these features and give them to the algorithm as input data. This way, the machine learning algorithm would perform a classification of the image. That is, in machine learning, a programmer must intervene directly in the classification process. In the case of a deep learning model, the feature extraction step is completely unnecessary. The model would recognize these unique characteristics of a car and make correct predictions-completely without the help of a human [5].

The second great advantage of deep learning is it's powered by massive amounts of data – deep learning models increase their accuracy with the increasing amount of training data, depending on the neural network size (more in the Figure 5).

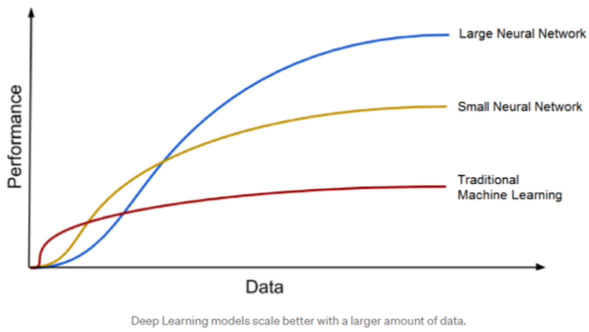

FIGURE 5. Data amount for deep learning [1].

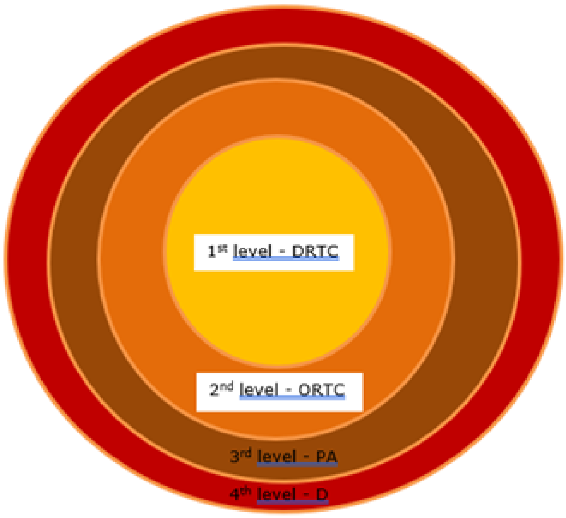

FIGURE 6. The model of the four deep learning levels.

3. Results and Discussion

To implement the deep learning process to the railway operational apps, it is necessary to define more learning levels based on the application type. The operation applications could be divided into direct railway traffic control (DRTC), operational railway traffic control (ORTC), planning applications (PA) and diagnostics (D) – the model of the four deep learning levels is in the Figure 6.

The core and the first level are the applications for direct railway traffic control (DRTC), it means digital documentation of traffic control with automatic train operation (ATO) potential, including ATO over ETCS. The first level of deep learning should include these data streams:

- mutual DRTC communication in TSI form (in all locations of the controlled area),
- DRTC and ORTC communication (DRTC behaviour based on the incoming ORTC data),
- DRTC and diagnostics systems communication,
- DRTC and safety equipment (incl. ETCS) communication,
- DRTC and IP telephony communication (incl.

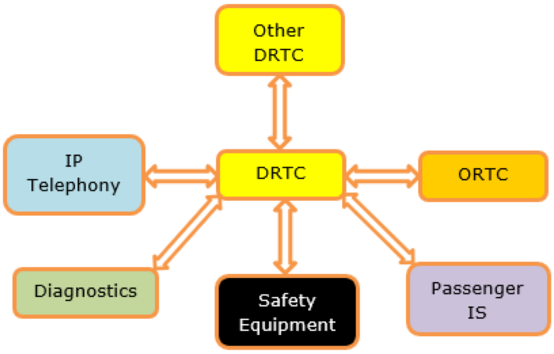

Figure 7. The simplified communication architecture of DRTC.

VoIP),

- DRTC and passenger IS communication.

The goal of the first level of deep learning is to create reliable application for DRTC with all automation functions. It could be e.g. ATO over ETCS – system controlled by artificial intelligence with possibility, but no necessity of operational staff intervention [6]. The simplified architecture is shown in the Figure 7.

In this first deep learning level are combined at the input all the data streams creating various rail traffic control situations. It could be like the learning from the dispatcher decision's recording plus knowledge of all other components status and behaviour (diagnostics, safety equipment, IP telephony etc.). The learning must be done on the real traffic data (e.g. for one timetable duration, it means 365 days). The output should be the optimized railway traffic control in the entrusted area of attraction including passenger information providing and ETCS, resp. ATO control.

The second deep learning level are the apps for operational railway traffic control (ORTC), it means integration platform of DRTC datasets (data aggregation) for larger areas (the entire state network and more). It should include these data streams:

- ORTC communication with all DRTC (it should be limited to the controlled areas),
- ORTC with planning application (train routing, capacity allocation),
- ORTC with railway undertakings requests and information systems (train composition etc.).

The goal of the second level of deep learning is to create the smart railway traffic control (SRTC) – the central communication hub (all DRTC data) with neural network support. In this level should be possible to control and optimize all train routes in the network (national/international). The main goal should be lowest delay in the network. The simplified architecture is shown in the Figure 8.

In this second deep learning level are combined at the input all the important data for railway traffic control in the entrusted network. It should be the learning

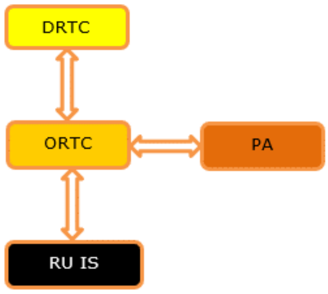

Figure 8. The simplified communication architecture of ORTC.

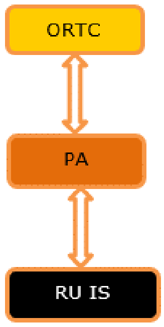

Figure 9. The simplified communication architecture of PA.

from the operational dispatcher decision based on the DRTC data and track dispatcher experience. The learning must be done on the real traffic data (e.g. for one timetable duration, it means 365 days). The output should be optimized railway traffic control in the network, ensuring the transfer of passengers and goods and the network delay minimization [7].

The third level of deep learning are the **planning applications (PA)**, it means applications for allocation of capacity and train routing. It must communicate with these systems:

- PA with ORTC,
- PA with railway undertakings requests and information systems (capacity allocation).

The goal of the third level of deep learning is to optimize the allocation of train routes based on the solution of previous operation situation. The main aim is the most train routes number with the lowest delay prediction. The simplified architecture is shown in the Figure 9.

In the third deep learning level are combined at the input all the train routes planning data solved in the infrastructure manager system (with the source of RU IS) and the solution from the second deep learning level. It should be the learning from the capacity allocation dispatcher decisions and the RU dispatcher revisions. The learning must be done on the real traffic data (e.g. for one timetable duration, it means 365 days). The output should be the optimizing of quality and quantity of all train routes, it means the

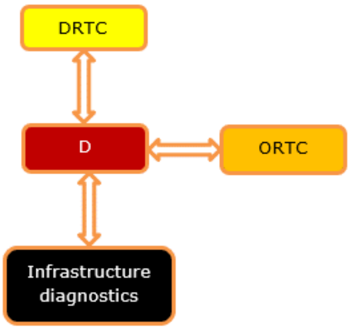

Figure 10. The simplified communication architecture of D.

combination of the most train routes number with the lowest delay prediction (network parameter) [8].

The final level of the defined deep learning process are the diagnostics apps (D). It must cooperate with these data streams:

- D with ORTC – summarization of operation failures and disorders (ICT, safety equipment),
- D with DRTC – detailed description of failures and disorders,
- D with infrastructure diagnostics (number of turns, traction consumption size etc.).

The main aim of this level is to predict the failures and disorders and suggest the infrastructure constraints with the operation impact (connection to DRTC and OPTC). The simplified architecture is shown in the Figure 10.

In the fourth deep learning level are combined at the input all the data from the first and second level of deep learning connected to the real infrastructure diagnostics data. It should be the learning from real failures and disorders and their traffic impact [9, 10]. The output should be the prediction of failures (maintenance intervals, replacement requirements) with the impact to all three previous levels of deep learning.

The all four levels of deep learning affect the others and therefore it must be operated as one IS. Moreover, it is necessary to keep the restrictive conditions, especially the unified network (unified topology) and security issues. The unified network must contain all the relevant data (line tables etc.) and it must distribute the same data correctly in all applications and systems. About security issues – the safety integrity level, the critical information infrastructure conditions and other cyber security rules must be followed. The threats like data poisoning must be mitigated.

4. Conclusions

Railway 4.0 should be based on digitization. In the area of operational applications, it could be created railway traffic control 4.0 (RTC 4.0), it means smart railway traffic control (SRTC). The use of artificial intelligence is recommended – the four levels of deep learning process was defined in this article.

The first level operates with railway station data, the second level with the aggregated area data, the third level with the capacity allocation data and the fourth with diagnostics datasets. The main goal of the four-level deep learning process is to define the operational applications staff behaviour and to optimize the railway traffic control process. The four-level deep learning process powered by massive amounts of data (big data should be used) could achieve very good RTC process results. The increase of reliability, security and safety should be reached.

Moreover, the power of SRTC is the possibility of the origin of European railway traffic control based on the RNE data and supported by co-financed development (European funding).

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References

[1] A. Opperman. Artificial intelligence vs. machine learning vs. deep learning. [2022-03-22], `https://towardsdatascience.com/artificial-intelligence-vs-machine-learning-vs-deep-learning-2210ba8cc4ac`.

[2] J. Široký, P. Nachtigall, E. Tischer, J. Gašparík. Simulation of railway lines with a simplified interlocking system. *Sustainability* **13**(3):1394, 2021. `https://doi.org/10.3390/su13031394`

[3] M. Bažant, J. Bulíček, P. Krýže, P. Veselý. Calculation of the capacity of switch area within railway stations with the use of simulation methods. In *Proceedings of the European Modeling and Simulation Symposium*, pp. 316–322. 2017.

[4] P. Nachtigall, J. Široký, E. Tischer. Assessing the efficiency of increasing the track speed in the line section Rokycany–Plzeň hl. n. *Sustainability* **12**(18):13, 2020. `https://doi.org/10.3390/su12187415`

[5] N. Mondek, J. Bulíček. Changes in the traffic situation on city roads after traffic diversion outside the city. In *International Conference on Traffic and Transport Engineering (ICTTE)*, pp. 1064–1072. 2018.

[6] E. Tischer, P. Nachtigall, J. Široký. The use of simulation modelling for determining the capacity of railway lines in the Czech conditions. *Open Engineering* **10**:224–231, 2020. `https://doi.org/10.1515/eng-2020-0026`

[7] P. Nachtigall, M. Škárek. Railway infrastructure capacity management for ad-hoc trains on the SŽDC network. *Acta Polytechnica CTU Proceedings* **5**:44–46, 2016. `https://doi.org/10.14311/APP.2016.5.0044`

[8] V. Cempírek, P. Nachtigall, P. Novák, M. Pluhár. The comparison of public road & railway transport costs. In *Proceedings of the 3rd International Conference on Traffic & Transport Engineering ICTTE*, pp. 855–860. 2016.

[9] V. Zitrický, J. Gašparík, L. Pečený. The methodology of rating quality standards in the regional passenger transport. *Transport Problems* **10**(SE):59–72, 2015. https://doi.org/10.21307/tp-2015-062

[10] M. Dedík, V. Štefancová, J. Gašparík, et al. Traffic capacity assessment of the selected track section on the slovak railways network after the implementation of ETCS L3 based on signaling principle. *Applied Sciences* **12**(11):5597, 2022. https://doi.org/10.3390/app12115597