COMPARING ABILITY OF GENERALISATION FOR METHODS SOLVING DECISION MAKING PROCESSES WITHIN SIMULATION MODELS OF PASSENGER RAILWAY STATIONS

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Abstract

The paper compares methods that support decision making processes within passenger railway stations. We focus mainly on problem of platform track assignment problem that occurs in cases of arrival trains delay. We compare ability of (i) mathematical methods related to multiple-criteria evaluation and (ii) artificial neural network (perceptron network) generalization for various periods of simulation time (morning and afternoon peak time) in this paper.

Keywords: Simulation, Neural network, Mathematical methods, Transportation.

Presenting Author's Biography

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1 Introduction

Implementation of decision-making supports and their proper integration into the simulation models represents quite challenging problem. The solution of that problem influences the credibility of the entire model. First, decision-making problem of platform track assignment occurring within passenger railway stations is presented. Next we focus on solved situations within our research using two methods: (i) mathematical methods related to multiple-criteria evaluation and (ii) artificial neural network (perceptron network). Finally we will introduce results and also comparison one method to the other.

2 Track assignments to delayed trains

Assignment of platform track to an arriving train represents a typical decision making task for dispatchers within passenger railway stations. If the inbound trains follow the timetable, the platform tracks are commonly assigned according to a priori created plan. In the case of a delayed arriving train the dispatcher is supposed to make an operative decision (potentially considering a set of substitutive tracks) about a relevant platform track assignment.

The above mentioned assignment problem should be properly solved also within particular simulation models. This is important for example, in the case of investigations focused on passenger stations suffering from frequent delays of arriving trains. Assigned tracks ought to correspond to resulting decisions made by experienced station dispatchers in reality. After assigning a platform track to a relevant train many other specialised algorithms (involved within a simulation model) are carried out (e.g. an algorithm focused on a setting train route respecting the rules of an interlocking system, an algorithm calculating the dynamics of the train movement to the assigned platform etc.).

A station dispatcher (managing real railway traffic) partially subjectively evaluates potential platform tracks that are suitable for an assignment to a delayed incoming train. The ultimately assigned track represents the best solution according to the expert knowledge of a particular dispatcher using certain criteria. The same strategy is applicable for a relevant simulation model. The first stage of the original submitted approach is focused on delayed trains from one arrival direction only. Platform track selection is primarily related to construction of an a priori track set, the elements of which can be admissibly assigned to a considered (delayed) inbound train. The tracks contained in the mentioned set are determined with regard to the defined arrival and departure line track. The sets can be further reduced according to the specific conditions (e.g. some elements/tracks are removed from the relevant set because of their insufficient length with respect to the considered train etc.).

The next step is associated with the final selection of a particular platform track (from an a priori set), which represents the most suitable solution (according to specific criteria) for the considered train in time of its real arrival. The mentioned criteria take into account the knowledge of station dispatchers and are formed as follows:

A : Track vacancy degree at the moment of train arrival.

B : Track vacancy period with regard to station sojourn time of an arriving train.

C : Occupation of the neighbouring track at the same platform (owing to the selected track) by a connection train.

D : Further technical and technological preferences of the track in respect to an arriving train.

A specified track assignment problem is obviously connected with multiple-criteria decision making focused on selection of variants (Figueira et al. 2004). The finite set of variants corresponds to the above mentioned a priori track set containing the tracks, which stand as candidates for a relevant assignment. If the criteria are at our disposal (A, B, C, D) and it is possible to calculate the criterion values (the relevant calculation is described in (Bažant and Kavička 2009)) of investigated decision variants then a criterion matrix can be created. An element of criterion matrix y_{ij} expresses the value of a criterion i (where $i = 1, 2, \ldots, 4$ reflects criteria $A, \ldots, D$) for the relevant variant/track k_j. The mentioned matrix can be formalised as follows.

$$\begin{array}{c|cccc} & k_1 & k_2 & \cdots & k_m \\ \hline A & y_{A1} & y_{A2} & \cdots & y_{Am} \\ B & y_{B1} & y_{B2} & \cdots & y_{Bm} \\ C & y_{C1} & y_{C2} & \cdots & y_{Cm} \\ D & y_{D1} & y_{D2} & \cdots & y_{Dm} \end{array} \tag{1}$$

3 Problem solving methods

Different approaches are applied for solving the mentioned problem. Mathematical methods related to multiple-criteria evaluation focused on selection of variants are based on primary subjective expert evaluations (considering criteria importance), which are further processed according to a particular method. Another approach is to use artificial neural network applying supervised learning which represents also one of the possible ways of solving the discussed track assignment problem.

3.1 Neural network – perceptron

One of possible way of solving the discussed track assignment problem is artificial neural network applying supervised learning (Nguyen et al. 2003). The mentioned neural network requires a prearrangement of two sets: a set of specific individual traffic situations (training patterns/inputs) and another set of relevant expert solutions. Produced outputs of a trained neural network are then compared with corresponding expected solutions - an expert/supervisor continuously evaluates the quality of the outputs and decides upon the next training steps.

Selection of an appropriate neural network type (e.g. feed-forward network, multilayered perceptron etc.)

represents an essential problem. It is quite difficult to determine the suitable kind of neural network (concerning a given problem) in advance. Thus, experiments with different kinds of neural networks and their diverse parameterisations were carried out. As a result of the experiments it was claimed that a two-layered perceptron produced the most encouraging outcomes.

The above mentioned methodological approach can be divided into the following steps:

- Gaining knowledge about the platform track assignment problem.
- Specification of the calculation method applied to getting criteria (A–D) values.
- Computation of criterion matrices (exploiting criteria A–D) for different traffic situations.
- Separation of available data into disjoint sets (training set and test set).
- Supervised learning of selected neural network using data from the training set.
- Evaluation of the neural network behaviour in respect to input data from the test set.

A two-layered perceptron was trained, tested and then applied to platform track assignments for arriving trains within the simulation model reflecting the system of a passenger station.

3.2 Mathematical methods

Most of multiple-criteria methods for decision making need information about relative particular criterion importance that we can express with criterion weights:

$$w = (w_a, w_b, w_c, w_d) \tag{2}$$

$$\sum_{i=A}^{D} w_i = 1; w_i \geq 0 \tag{3}$$

The higher the criterion importance is, the weight of the criterion is higher as well. To obtain criterion weights from user or from expert is not so easy but there are some methods that are able to calculate criterion weights on the base of some easier subjective information from user.

Then we can calculate final assessment O_k of track k with following formula where y_{ik} is value of criterion i for track k and w_i is weight of criterion w_i.

$$O_k = \sum_{i=A}^{D} y_{ik} * w_i \tag{4}$$

There are couple of mathematical methods to determine criterion weights and here are listed some of them:

- sequence method,
- points method,
- pair comparison method – Fuller method,
- quantitative pair comparison method of criterions,
- weight calculation based on geometrical mean of rows,
- Saaty method.

Due to paper limit it is not possible to introduce all listed methods of calculation weights, in addition it is not problem to find methods explanation in literature. Further on we will present results that were obtained using Saaty method that provide best results [1] in comparison with another listed methods.

To get results using Saaty method we considered paired comparison matrix (5) because we received best results using it. Hit rate using this matrix is denoted in chapter 5.

$$\begin{array}{c|cccc} & A & B & C & D \\ \hline A & 1 & 1 & 9 & 9 \\ B & 1 & 1 & 9 & 9 \\ C & \frac{1}{9} & \frac{1}{9} & 1 & 9 \\ D & \frac{1}{9} & \frac{1}{9} & \frac{1}{9} & 1 \end{array} \tag{5}$$

4 Considered situations

The selection of Prague main station as a testing case took into account (a) the number of platform tracks, (b) the number of trains approaching the station within peak hours, (c) good knowledge of local operational conditions (especially related to control and decision-making processes).

Fragment of infrastructure is depicted on figure 1 and attention was paid to infrastructure and train information relevant to timetable 2009/2010. Figure 2 include information about input/output tracks (Pv_1, Pv_2, Vs_1, Vs_2, Vs_3, Vs_5, Li_1, Li_2, Ho_1, Ho_2), number and length of platform tracks (k_{13a}, k_{11a}, k_9, k_7, k_1, k_2, k_8, k_{14}, k_{20}) and according to infrastructure design we also respected feasible track sets regarding input and output track of trains. According to figures it is also obvious that platforms are divided into two parts in reality. We had to merge these tracks to one single track to be able to produce criterion matrices respecting real times of track occupancy. So this adjustment was taken into account only in our model and this adjustment does not misrepresent real traffic situations.

Traffic peak time (6.00–9.00 a.m.) was investigated in order to calculate hit rate of mathematical methods and also hit rate of artificial neural network. Delayed trains arriving within the frame of that rush period cause the most serious problems (compared with the rest of the day) connected with platform track assignment.

One arrival direction was chosen to inspect neural network sufficiency of a correct track assignment. Local

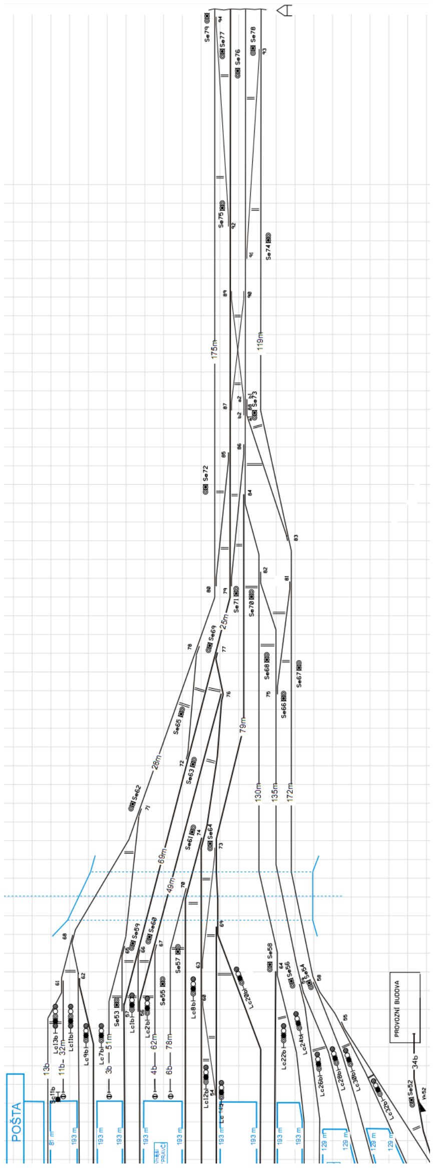

Fig. 1 Track layout of an investigated station

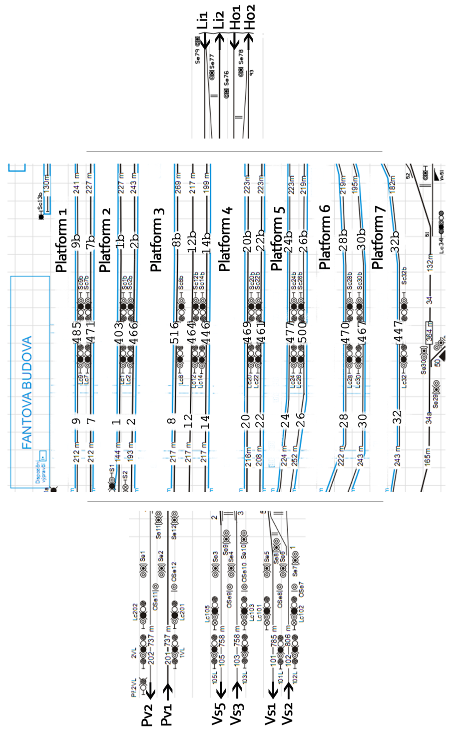

Fig. 2 Detail of platform tracks

station dispatchers recommend taking the arrival direction from Olomouc–Kolin (input track Li_1), which disposed of the highest number of delayed trains from all arrival directions concerning the studied station.

Five long distance trains arrive at Prague main station using the mentioned arrival track during morning rush hours, so corresponding criterion matrices for all these trains were evaluated. For these trains we simulated delay from 0 to 60 minutes with step of 1 minute, while all other trains were considered running on time.

Different delay values of arriving trains are connected with diverse traffic situations depending on time. This way we elaborated 305 criterion matrices (different traffic situations) and expert determined a platform track that would be assigned in reality.

The linearly ordered initial set of applied data was divided into the two following disjoint subsets:

- Training subset (153 situations with sampling period set to 2 min).
- Testing subset (152 situations with sampling period set to 2 min, phase shift was equal to 1 min).

The process of training neural network proceeded with data from training set. The neural network was able to learn all patterns after applying a reasonable number of learning epochs (fig. 3).

Next, the network was tested using data inputs from the test set. The testing stage reached 92 per cent hit ratio

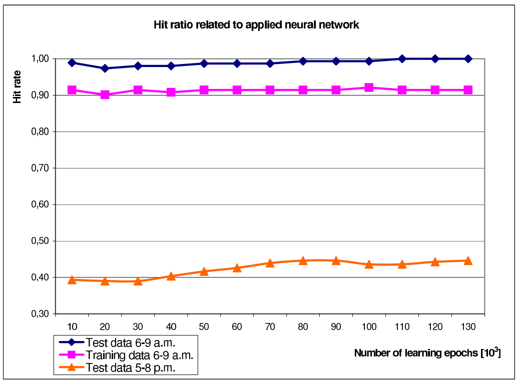

Fig. 3 Hit ratio trends of neural network depending on learning epochs

comparing the network outputs and expert expectations which is very good result.

All data (305 traffic situations) were also calculated using mathematical methods, especially using Saaty method reflecting paired comparison matrix in (5).

Hit ratio using Saaty method for morning peak time was 91 per cent that is slightly worse result than using perceptron neural network.

Main benefit of this paper is to evaluate these two methods for situations that were not taken into account during process of calculating weight of neurons/criterion weights. Detail comparison of these two methods reflecting this condition is included in next section.

5 Methods comparison for just in time decisions

Results presented in previous chapter (hit rate over 90 per cent for ANN and also for Saaty method) are very good. These results reflect only situations that were considered during calculating weights of neurons and also during weight calculations for Saaty method.

Next step is to calculate hit rate for situations that were not considered during learning process and during weight calculations for Saaty method.

Table 1 shows results for these methods after setting weight to get maximum hit rate for training set of data and there are also results for situations that were not considered as training data and we can mark it as test data. Test data include trains from afternoon peak time (5–8 p.m.) arriving from the same direction as trains considered for producing training data and delay interval is also considered in range 0–60 minutes (the same as for morning peak time). This way we took into account 305 traffic situations that is the same number of situations as data considered for morning peak time.

Hit rate for training data set is better for ANN than for Saaty method and row number 1 shows that ANN is able to learn how to solve (using weights of hidden neurons) all situations that the ANN was trained for (hit rate is 100 per cent).

Tab. 1 Neural network (ANN) and Saaty method (SM) comparison

Data	*Method*	*Hit rate [%]*
Training data (6–9 a.m.)	ANN	100.0
Training data (6–9 a.m.)	SM	91.1
Test data (6–9 a.m.)	ANN	92.1
Test data (5–8 p.m.)	ANN	41.3
Test data (5–8 p.m.)	SM	96.1

In contrast Saaty method, using the best paired comparison matrix, results with much worse results (hit rate for training data slightly above 91 per cent) and the Saaty method gives the same results for test data selected for morning peak time – that is the reason why it is not presented in the table.

When we get to the data from afternoon peak time, we can see that ANN gives worse results in comparison with Saaty method. ANN was not trained to any situation from the afternoon peak time and ANN is not able to generalise for situations that the ANN is not trained for. That is the reason why the hit rate is only above 40 per cent. On the other hand Saaty method does not depend on any training data set (Saaty method depends only on paired comparison) and that is the reason why hit rate is almost the same or even better than for data from morning peak time (hit rate over 96 per cent).

6 Conclusion

There is presentation of comparison artificial neural network (perceptron) vs. Saaty method in this paper. The results show that ANN strongly depends on training data set while mathematical method for evaluation criteria weights (such as Saaty method) does not. This fact comes from these methods definition and we wanted to calculate this fact on real traffic situations.

Our future work will focus on a way how to get even better results using especially artificial neural network because using mathematical methods it is hardly likely to get 100 per cent hit rate.

7 References

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