Applying Airspace Capacity Estimation Models to the Airspace of Hungary

Bence Számel[1*], István Mudra[1], Géza Szabó[1]

Abstract

Estimation of airspace capacity in order to keep air traffic controller workload at an optimal level is essential for the safety of air traffic. In the past, several different methods were developed for airspace capacity estimation with different benefits and drawbacks. In our research we studied the applicability of one of these methods (based on a neural network model) in the airspace of Hungary. This paper presents a possible way of gathering and processing data and validating the results given by the model.

Keywords

airspace capacity, air traffic complexity, controller workload, neural network

[1] Department of Control for Transportation and Vehicle Systems,
Faculty of Transportation Engineering and Vehicle Engineering,
Budapest University of Technology and Economics
H-1521 Budapest, P. O. B. 91. Hungary

* Corresponding author, e-mail: szamel.bence@mail.bme.hu

1 Introduction

Managing the flow of air traffic in the safest and most effective way is a fundamental goal in today's Air Traffic Control (ATC) systems. The safety of air traffic can be measured in different ways (e.g. (Vismari and Camargo, 2011), (Skorupski, 2010) or (Zhang et al., 2012)). It is of high importance for the sake of both safety and efficiency that the traffic of a certain airspace be always controlled by a number of air traffic controllers most suitable to the actual traffic situation. In other words, the most important thing is to keep the air traffic controllers' workload at a level that is neither too high, nor too low as both kinds of these undesirable situations (especially those with high workload (Rodgers et al., 1998)) can lead to an increasing number of controller errors, which is unacceptable due to safety reasons. Furthermore in the case of low workload situations the requirement of efficiency can also be violated as the Air Traffic Control system does not operate at its maximum available capacity (there can be air traffic controllers that may take over the traffic handled by others). This makes it essential to estimate the controller workload generated by a certain traffic situation in a certain sector of the airspace as precisely as possible.

Nowadays in most Air Traffic Control systems – including the one in Hungary – the estimation of anticipated controller workload is done using a simple method based upon aircraft count. The workload however is not determined simply by the number of aircraft handled by the controller in scope as it is influenced by numerous other factors like the disposition of aircraft in the airspace, relative aircraft velocity and heading, aircraft types, size and shape of the sector, weather, availability and quality of ATC equipment etc. These are usually referred to as factors describing air traffic complexity or complexity factors for short.

Giving a description of airspace capacity using mathematical formulae can be achieved by evaluating the value of the complexity factors. This may seem simple but raises a couple of questions to which no unambiguous answers have been given so far. These questions include which of the possible complexity factors affect workload, how can the different factors be quantified and how can we describe the mathematical correspondence between complexity factors and controller

workload. In the past different researchers tried to give different answers to the above questions by developing different models for airspace capacity estimation. Some of these models will be reviewed briefly in Section 2.

As already mentioned, a more precise way of estimating air traffic sector capacity would be beneficial for the Air Traffic Management system of Hungary, managed by HungaroControl. The aim of the research presented below was to do a preliminary study about the possible future development of a decision support tool that could help ATC supervisors in making decisions of opening and closing sectors and/or airspace designers in determining the location of sector borders. The latter task demands more and more attention with the expected appearance of different dynamic sectorisation methods described in (Zelinski and Lai, 2011) in the near future.

Due to the preliminary aspect of the research, instead of trying to develop a new capacity estimation method, existing methods were parameterized according to the characteristics of the Hungarian airspace. After reviewing the existing models in Section 2 and selecting which one to use in Section 3, we discuss the complexity factors taken into account in Section 4. In Section 5 we describe how data was obtained to quantify the aforementioned complexity factors and how the quantification was implemented and finally in Sections 6 and 7 we validate the results given by one of the models and briefly present the possible future escalation of our study.

2 Existing methods of airspace capacity estimation

In past decades, several research parties were concerned with the mathematical description of sector capacity and as a result, multiple methods were developed to solve the problem (as shown in (Prandini et al., 2011)). A large set of these methods consists of the ones based on regression models. When using regression models, first the values of complexity factors for different air traffic situations have to be calculated somehow and then the workload generated by the situations in question has to be assessed. The assessment can be done by asking the subjective personal opinion of controllers (Kopardekar and Magyarits, 2003), by observing controllers at work and measuring the time they spend on various actions (Inoue et al., 2010) or by measuring their physiological parameters (Averty et al., 2002). Finally, regression techniques – which can be simple linear (Majumdar and Ochieng, 2002) or logistic regression (Masalonis et al., 2003) as well as more developed methods such as neural networks (Gianazza and Guittet, 2006) – are used to find the function that best fits the correspondence between complexity factors and workload. Once this function is defined, it can be used to estimate the level of workload induced by expected future traffic situations.

The biggest disadvantage of regression based methods derives from their overly elaborated way of describing complexity factors. On one hand, this leads to results precise enough for reliable future estimations in a certain airspace. On the other hand this prevents the models from being applicable to airspaces outside the one they were originally developed for. It is worth noting that the specificity of the models could probably be decreased by using simulation for the assessment of controller workload. This can mean simulated air traffic either handled by a human controller (similarly to the road vehicle driver simulation presented in (Mihály et al., 2012)) or a simulated controller (as presented in e.g. Skorupski, 2010). In the latter case however, a sophisticated model is needed to describe human behavior and operator tasks (e.g. the one given in (Martinie et al., 2010) or (Donath et al., 2010)) as well as operator workload (like the one proposed by Lee et al., 2011).

This shortcoming of regression models led to the emergence of other model types with a more general applicability. One of these is the model developed by Eurocontrol, which represents controller workload as a time value based on the hourly occurrence of certain controller macro activities and the average time required to execute them (Hilburn, 2004). The former can be calculated based on the complexity factors using software developed by Eurocontrol, while the latter are evaluated through a genetic algorithm. This model can be applied to any Eurocontrol airspace, although its simplicity means that its main scope is validating existing declared airspace capacity values based on experience.

A different way to increase the universality of the application of methods is developing models that simply focus on representing air traffic complexity with one single value (or a few values) instead of trying to define the relationship between traffic situations and the workload they generate. This model types include those that calculate traffic complexity on the basis of air traffic geometry (e.g. the distribution of aircraft in the airspace and their speed and direction related to each other) and those that model air traffic as a dynamic system and represent it with one characteristic system variable (Delahaye and Puechmorel, 2000). Another example of such simplified models is the „complexity map" model, that is also based on the geometry of air traffic and provides values of the necessary change of aircraft direction and velocity (thus giving the approximate level of controller workload) as a function of the position and flight direction of new aircraft entering the airspace (Lee et al., 2007).

The models introduced so far have one thing in common, particularly the fact that they all contextualize air traffic as a set of single aircraft. It is however also possible to model air traffic as a structure of air traffic flows and an example to this kind of modeling method is given in (Song et al., 2007). Using flows instead of aircraft as a basis for the model is not the only invention given by Song, Wanke and Greenbaum as they also emphasize using complexity factors that can be predicted with high reliability even on longer terms (e.g. 60-120 minutes). For the representation of the correspondence between the characteristics of air traffic flows and controller workload they use self organizing maps, which can be considered more advanced versions of the neural networks mentioned earlier.

Although not closely related to ATC sector capacity estimation, another example for flow based air traffic models is presented in (Péter and Szabó, 2012). This model gives a macroscopic approach to air traffic that is represented as a system of traffic flows with different speed and connections to each other. The model's purpose is to aid air traffic network optimization and as an optimal (or close to optimal) network leads to more predictable controller workload, it would possibly be helpful in the domain of airspace capacity research as well.

3 Selecting the proper method

When selecting the proper method for the study that focused on Hungarian airspace, multiple aspects were taken into consideration. The long-term goal is the development of a model (and software based on the model) that could serve as a decision support tool in choosing the optimal number of sectors (and sector configuration) as well as designing sector borders in case of airspace refactoring. Keeping this in mind, the results need to be accurate enough for the model to be used for more than just the validation of existing sector capacity numbers. General applicability would also be helpful but this is not a highly important aspect at the moment. A short-term goal of our study is however to assess the possibility of adapting one of the aforementioned model types to the airspace of Hungary using a relatively small amount of resources and verify the accuracy of the results in order to decide whether it is worth going on with the research. With all the above considered, regression based models seemed the most suitable and our final choice fell on the model based on neural networks and the method used to carry out the study was heavily based on the one described in (Gianazza and Guittet, 2006).

The actual neural network had three layers, one input, one output and one hidden layer. The values of the input layer were derived from the values of complexity factors by performing a principal component analysis. The output layer had three nodes, each representing a potential state of air traffic control sectors („merged" meaning the sector is merged with others, „split" meaning the sector is split in multiple sectors and „armed" meaning the sector is neither merged nor split). The values on the output nodes (real numbers between 0 and 1) represented the „optimality" of the given state in the given traffic situation (with the highest number belonging to the optimal state according to the model).

4 Defining applied complexity factors

Former research publications of similar topics mention more than a hundred types of variables that could be used to describe air traffic complexity. Due to this enormous amount of complexity factors – no matter if we work on creating a new model or parameterizing an existing one – it is highly advisable to decrease their number by selecting which of them do we really need for our study. By selecting needed complexity factors, the characteristics of the airspace and air traffic control system in scope

should be considered (even though this leads to a decrease in the model's applicability to other airspaces) and meanwhile using of complexity factors that have a similar meaning ought to be avoided. One possible way of selecting complexity factors could have been using an already assembled set from a former study (like the 19 complexity factors used by (Vogel et al., 2013)), but we chose to gather information from experts with a detailed knowledge on the airspace and air traffic of Hungary instead.

In the case of the neural network model parameterized to Hungarian airspace, the complexity factors to be used were selected following consultation with active air traffic controllers, supervisors and ATC operations experts of HungaroControl. These consultations were carried out through personal interviews as well as a questionnaire asking the controllers' subjective opinion on the contribution of certain complexity factors to workload. Based on the results of this survey, the following complexity factors were used in the model as input parameters (the symbols representing the given parameters in the neural network model can be seen in parentheses).

- Number of aircraft in the given sector (AcCnt)
- Number of climbing aircraft in the given sector (AcCntCl)
- Number of descending aircraft in the given sector (AcCntDesc)
- Percentage of climbing aircraft in the given sector related to all aircraft (AcCntCl%)
- Percentage of descending aircraft in the given sector related to all aircraft (AcCntDesc%)
- Deviation of aircraft speed in the given sector (SpdDev)
- Balance of spatial distribution of aircraft in the given sector (Dens)
- Convergence of traffic in the given sector (Conv)
- Divergence of traffic in the given sector (Div)
- Insensibility of convergent traffic in the given sector (InsPos)
- Insensibility of divergent traffic in the given sector (InsNeg)
- Number of aircraft pairs in conflict (ConfNo)
- Number of standard flight route intersection points in the given sector (IntsctNo)
- Number of standard flight levels in the given sector (FLNo)
- Number of unused standard flight levels in the given sector (FreeFLNo)
- Number of special airspaces open in the given sector (TRANo)
- Number of aircraft in Budapest TMA (TMACnt)

In order to use such factors in a mathematical model, first their exact meaning has to be defined (e.g. when do we consider two aircraft to be in conflict) and they have to be enabled to be represented numerically. In the case of some types of complexity factors (like the number of descending or climbing aircraft

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in the given sector) this can be done unambiguously and without using complex mathematical formulae, while in other cases a proper formula has to be defined to calculate the factor's value and it can often be achieved in multiple ways. The mathematical formulae used to calculate complexity factors' values in this particular study will be specified in Section 5 along with the actual calculation of the values, that can be considered the final step in the process of describing complexity factors.

5 Obtaining and processing data for the model

The data necessary to calculate the values of complexity factors and validate the neural network model can be divided into three groups:

- radar data of traffic situations in scope
- airspace structure related data (borders of sectors and special airspaces)
- subjective data of controller workload generated by the traffic situations in scope (in other words, the optimal number of sectors in different situations)

In the current study, HungaroControl served as the source of all three kinds of data in a direct or indirect way (data related to sector and special airspace borders were obtained via the Department of Control for Transportation and Vehicle Systems of Budapest University of Technology and Economics). Radar data was provided for two different 24 hour periods (28th July 2011 and 29th July 2012) and for a further 6 hours from periods, when military restricted airspaces were open in Sector E (the eastern block of the airspace). The latter was necessary for the model to handle the effect of open special airspaces on the controllers' workload. Once the radar data was available, it was sampled every 30 minutes, which resulted in a total amount of 107 air traffic situations used in the model.

With the obtaining and sampling of radar data finished, it became possible to quantify the complexity factors. The radar data related to a single flight can provide the following information (after executing the necessary transformations): geographical position of the flight (latitude and longitude coordinates), flight level, heading and ground speed. The sector in which the aircraft is located at the given moment can be determined based on the data of the aircraft's geographical position and the position of sector borders using a „point-in-polygon" algorithm based on (Galetzka and Glauner, 2012). This provides a relatively easy way of calculating aircraft count in basic sectors (sectors that cannot be split), while the aircraft count in sector blocks (blocks of airspace consisting of multiple basic sectors) will be the sum of aircraft in the appropriate basic sectors.

When trying to calculate the number of climbing or descending aircraft a problem can occur due to the lack of information on vertical aircraft speed contained in the radar data. To eliminate this problem and get information on flight level changes, a second sample was taken for every sample of radar data with a short time difference (about one minute in particular) therefore, differences in flight level data of coherent traffic situations indicated that the given flight is climbing or descending. Once we know, which flights change flight level, their number in a certain sector can be calculated by simple addition. Percentage of such aircraft related to all flights can also be obtained by simple percentage calculation. The flights' speed deviation was calculated using the following formula (with N standing for the number of flights, v_i for the speed of flight i, v_m for the mean value of flight speeds and σ for standard deviation):

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(v_i - v_m\right)^2} \qquad (1)$$

Unlike the ones mentioned earlier, this calculation has to be done for all possible combinations of basic sectors.

Quantifying complexity factors representing traffic geometry (Dens, Div, Conv, InsPos and InsNeg) is based on the model created by Delahaye and Puechmorel using the following formulae (Delahaye and Puechmorel, 2000).

Calculation of traffic density:

$$Dens\left(i\right) = 1 + \sum_{\substack{j=1 \\ j \neq i}}^{N} e^{-\infty\frac{\left\|\overline{d_{ij}}\right\|}{R}} \qquad (2)$$

Where N is the number of aircraft in the given sector, $\left\|\overline{d_{ij}}\right\|$ is the norm of the distance vector of aircraft i and aircraft j, α is a weighted coefficient (1 in the model applied to Hungarian airspace) and R can be considered the radius of the aircraft's environment taken into account in the model (we used 50 NM). Dens(i) belongs to a single flight (flight i) and represents the density of aircraft in its environment. Density for an entire sector can be obtained by adding the respective Dens(i) values for each flight in the sector. The greater the sum of these values means that the traffic is more erratic and it is possibly concentrated in small, high density areas throughout the sector.

Calculation of traffic convergence and divergence:

$$Conv\left(i\right) = \sum_{\substack{j=1 \\ j \neq i}}^{N} \left|\frac{d\left\|\overline{d_{ij}}\right\|}{dt}\right| \cdot 1_{R^-}\left\{\frac{d\left\|\overline{d_{ij}}\right\|}{dt}\right\} e^{-\infty\frac{\left\|\overline{d_{ij}}\right\|}{R}} \quad (3)$$

$$Div\left(i\right) = \sum_{\substack{j=1 \\ j \neq i}}^{N} \left|\frac{d\left\|\overline{d_{ij}}\right\|}{dt}\right| \cdot 1_{R^+}\left\{\frac{d\left\|\overline{d_{ij}}\right\|}{dt}\right\} e^{-\infty\frac{\left\|\overline{d_{ij}}\right\|}{R}} \quad (4)$$

In order to calculate convergence and divergence, one needs the relative speed of aircraft besides the aforementioned α and R values. 1_{R}- and 1_{R}+ are the indicator functions of negative and positive real numbers respectively. These functions are necessary in the formula to ensure that only flights approaching the given aircraft are taken into account when calculating convergence and only those flying away when calculating

divergence. This prevents convergence and divergence in the same sector from eliminating each other and causing the illusion that all aircraft have the same heading. As both (3) and (4) provide values for single aircraft, summation is needed to get the values for the entire sector.

Insensibility is calculated from traffic sensitivity using the following formula:

$$ISt_+(i) = \frac{1}{\varepsilon + St_+(i)} \; and \; ISt_-(i) = \frac{1}{\varepsilon + St_-(i)} \qquad (5)$$

Where St_+ and St_- represent the sensitivity of the air traffic's convergence and divergence to the changes in aircraft speed and heading (in other words, sensitivity to the controller's orders). $St_+(i)$ and $St_-(i)$ can be calculated similarly to Conv(i) and Div(i) respectively by substituting $\left| \frac{d\|\overline{d_{ij}}\|}{dt} \right|$ in the formula with the gradient vector norm $\left\| \overline{\nabla_{\|\overline{d_{ij}}\|}} \right\|$. The value ε of appearing in (5) had a constant value of 1 during the calculations related to the neural network model.

When a sector capacity estimation model is based on historic data – like it is in our case – one of the most difficult tasks in parameterizing the model is quantifying the occurrence of conflicts among aircraft. The difficulty arises from the fact that most traffic situations read from radar data are seemingly conflict free as under usual circumstances in operation, air traffic controllers observe and resolve potential conflicts before they would turn into actual conflicts. This leads to uncertainty when analyzing historic radar data, since it cannot be decided if the situation was conflict free by default or it had numerous conflicts that were resolved in time by the controller. It is however still possible to make estimations on the prevalence of conflicts in a given traffic situation. One relatively easy way to do so is to determine which pairs of flights move on the same flight level and on intersecting routes (presuming that none of them change heading or flight level) and which of these shall reach the intersection point in relatively short time (e.g. 15 minutes) and with short time difference (e.g. 5 minutes) to each other (presuming that they will not change their speed). When parameterizing the neural network model, we refer to this value as the „number of conflicts" although it does not equal the actual number of conflicts but a value that represents the prevalence of conflicts.

Determining the number of standard route intersections in different sectors was accomplished using simple geometric calculations (calculating intersection point coordinates for two lines, each given by two points) and the aforementioned „point-in-polygon" algorithm (to determine if the given intersection point is in the sector or not). As neither the sector- nor the route structure of the airspace did change throughout the time period in scope, the above calculations need to be performed only once for every sector. Obtaining the number of flight levels and unoccupied flight levels in a sector does not need complicated calculations either. The former is done by simply counting the flight level values divisible by ten between the lower and upper border of the sector and latter by subtracting the number of levels that include at least one flight from the total number of levels.

When evaluating the number of special airspaces in sectors, one should mind that controller workload is usually influenced not only by the number (and size) of open airspaces in the given sector but also by those open in neighboring sectors as they can have an influence on the traffic in the given sector too. In the case of our neural network parameters, the number of special airspaces in neighboring sectors were taken into account through multiplication by 0,5. Number of aircraft in the TMA are calculated similarly (using „point-in-polygon" algorithm) to the number of aircraft in the given sector.

All the above calculations were realized by our own software created by using .Net C# environment for development. For each sample of radar data, calculations were made to the entire airspace, ten basic sectors (marked: WL, WM, WU, WH, WT, EL, EM, EU, EH, ET) and twenty sector blocks consisting of multiple basic sectors but not covering the entire airspace (marked: W, WLM, WLMU, WLMUH, WMU, WMUH, WMUHT, WUH, WUHT, WHT, E, ELM, ELMU, ELMUH, EMU, EMUH, EMUHT, EUH, EUHT, EHT). In our model, we used three different networks for the entire airspace, basic sectors and sector blocks. This was necessary as the former two can only have two states (the whole airspace cannot be merged with anything and basic sectors cannot be split) meaning two nodes in the output layer, while the latter can have all three possible states, which results in three nodes in the output layer.

In order to reduce the necessary number of nodes in the input layer of the network, a principal component analysis should be performed on the available data before the neural network calculations are done. By doing so, instead of the actual complexity factors, we can use principal components as input parameters, thus representing the input values with less different variables. We decided to perform the neural network simulation for each sector type (airspace, basic sectors and sector blocks) by using the principal components with the highest significance (i.e. components with an eigenvalue greater than 1). This resulted in the usage of the first 4 principal components for the network representing the airspace, the first 5 for the one representing basic sectors and the first 6 for the one representing sector blocks. We also performed calculations with a higher number of principal components when the results seemed to be inaccurate and with a lower number when they were proven to be accurate.

Data to be used in the input layer is obtained by the aforementioned method, but in order to train the neural network, we need data for the output layer too. The output layer includes two or three nodes depending on whether we want it to be used for the entire airspace, basic sectors or sector blocks. The value placed on the output nodes in the learning stage of the network

is 1, exactly when the given node represents the optimal state of the given sector („merged", „split" or „armed") in the given traffic situation. Simultaneously, the value of the other node or other two nodes is 0. For example, if a sector block has such a high traffic complexity that it should be split, then its „split" node will have a value of 1 while its „merged" and „armed" nodes will have 0. The optimal state of sectors in different traffic situations can be determined based on the optimal sector configuration of the airspace. In our model, these optimal sector configurations were obtained by asking the subjective opinion of active ATC supervisors on the traffic situations. To get information about these opinions, radar pictures displaying the situations in scope were shown to some supervisors working for HungaroControl and they were asked to use their work experience and tell, how many air traffic controllers would be needed to handle the given situation and which sector borders should be used. It is important to mention, that this way of gathering information has a drawback (besides subjectivity). When asked, supervisors give their opinion on the traffic of the entire airspace and do not take into account each possible basic sector and sector block out of its environment. This means that in some situations, certain basic sectors or sector blocks could be merged with others according to their own traffic but the merging is not possible due to the traffic of neighboring sectors. In such cases the given sectors optimal state in the model appears as „armed" even though the optimal state in reality would be „merged". This source of error has to be taken into consideration during the evaluation of the models results.

6 Results of the neural network model

Before analyzing the results, we briefly present how neural networks work in general. As mentioned earlier, neural networks have an input layer, an output layer and one or more hidden layers (one in our case) and each layer consists of nodes. Each node of the input and output layers represents an input or output variable, while nodes in the hidden layer (the number of which may differ) represent the logic inside the network through certain functions describing the correspondence between input and output variables. The nodes of each layer are connected to the nodes in the next layer and each of these connections have a weight representing the strength of influence of a given input variable to a given output variable through a given hidden layer function. The value of these weights is calculated in the so called training period of the network. In the stage of training, the network knows the output values belonging to the different combinations of input values and tries to optimize the weights in order to minimize the difference between calculated output values and the known values. Once training is finished, the network can use the calculated weights to provide output values for any given set of input values. Fig. 1 shows the structure of a neural network (in this particular case, the network created for the entire airspace, using the first four principle

components). The figure was created with the neural network displaying function of the neural network designer software we used and it shows the input-, hidden- and output layers from left to right respectively. The thickness of the edges connecting the nodes represents the weight belonging to the given edge. More detailed information about neural networks can be found in (Jordan and Bishop, 1997).
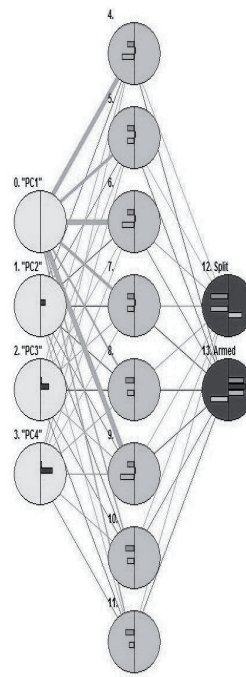

Fig. 1 Example of a neural network

Neural network calculations were performed using the software EasyNN-plus developed by Neural Planner Software. The software does not allow the user to change the logic inside the network, but provides lots of configuration options for learning and validating (testing during the learning process) functions of the network.

All of the data calculated through the method described in Section 4 was used during the neural network modeling. About 60% of the available input data was used in the learning of the net and 20% was used for validation while learning. The remaining 20% was used for the evaluation of the results. Besides the data unknown to the networks, the same data used for training and validating was used again in the evaluation process. The usual conditions that had to be fulfilled for the network to stop automated learning was that at least 95% of the output values used for validation must be within +/- 5% range of the expected value. In a few cases it was also necessary to give a time limit to the learning process due to the lack of accuracy in the results.

Results of the neural network model for the entire airspace can be seen in Table 1. The first column shows the number of principal components used (in other words, the number of input layer nodes).

The second column marks the type of data used for evaluating the results. Q stands for query and means that the results in the given row were obtained with query data that was not used during the training of the network while T stands for training and means that the same data was used for evaluation and training. The rest of the columns represent the number of all cases and the number of cases (with absolute and percentage values) in which the results were identical to the expected ones.

Table 1 Results of the model for the entire airspace

Principal components	Evaluation data	All states		
		All	Correct	Correct%
1	Q	21	21	100
1	T	65	64	98,46
4	Q	21	21	100
4	T	65	65	100
		Split		
		All	Correct	Correct%
1	Q	18	18	100
1	T	57	56	98,25
4	Q	18	18	100
4	T	57	57	100
		Armed		
		All	Correct	Correct%
1	Q	3	3	100
1	T	8	8	100
4	Q	3	3	100
4	T	8	8	100

Table 2 Results of the model for basic sectors

Principal components	Evaluation data	All states		
		All	Correct	Correct%
5	Q	229	217	94,76
5	T	643	616	95,8
6	Q	229	217	94,76
6	T	643	616	95,8
10	Q	229	219	95,63
10	T	643	624	97,05
17	Q	229	221	96,5
17	T	643	629	97,82
		Armed		
		All	Correct	Correct%
5	Q	16	7	43,75
5	T	44	21	47,73
6	Q	16	11	68,75
6	T	44	35	79,55
10	Q	16	9	56,25
10	T	44	36	81,82
17	Q	16	9	56,25
17	T	44	36	81,82
		Merged		
		All	Correct	Correct%
5	Q	213	210	98,6
5	T	599	591	98,66
6	Q	213	206	96,71
6	T	599	581	97
10	Q	213	210	98,6
10	T	599	588	98,16
17	Q	213	212	99,53
17	T	599	593	99

The results in Table 1 show that the model works with high accuracy for the entire airspace even with only one principal component used. A slight decrease can be observed in accuracy in the case of validation with training data. This seems to be odd, because a neural network should provide more reliable results with already known data than unknown data. The most probable explanation for this supposes that the results have a small (1-2%) probability of error even for such an accurate network. This error probability however may not lead to any incorrect results when the number of test cases is so low as it was in the case of validation with query data, while it may do so when this number is increased to 65 as seen in the case of validation with training data.

Results for basic sectors are presented by Table 2 in a structure similar to Table 1.

According to Table 2, the model can be considered reliable for basic sectors too even when using only five or six principal components. The inaccuracy that can be seen in the case of „armed" sectors is not necessarily deriving from an error in the neural network model: they can also be explained by the problem mentioned in Section 4, particularly that some sectors can have „merged" as a an ideal state in the model while their state in reality is „armed" just because there are no other options

available. This inaccuracy can clearly be decreased by increasing the number of principal components involved.

Results for sector blocks are shown in Table 3.

Accuracy of the results for sector blocks is obviously much smaller than it is for the entire airspace or basic sectors. A certain decrease in accuracy is not surprising because the network has three output nodes and it may not be able to calculate the value of the weights in the hidden layer precisely enough so that the difference to the expected values is small enough for all three values in the output layer (finding the location of two borderlines between three states is much harder for the network than finding one between two). This alone however does not explain the results seen in Table 3, especially the extremely low (below 10%) accuracy produced for „armed" sector blocks. Further possible explanations can be found in the neural networks software implementation or the parameters of the model. Changing the logic of the network could possibly enable more effective learning, which would lead to better results but as mentioned earlier, the software used in our study does not allow this.

Table 3 Results of the model for sector blocks

Principal components	Evaluation data	All states		
		All	Correct	Correct%
6	Q	411	229	55,72
6	T	1323	949	71,73
17	Q	411	235	57,18
17	T	1323	955	72,18
		Split		
		All	Correct	Correct%
6	Q	136	93	68,38
6	T	451	398	88,25
17	Q	136	95	69,85
17	T	451	399	88,47
		Armed		
		All	Correct	Correct%
6	Q	44	2	4,55
6	T	174	13	7,47
17	Q	44	2	4,55
17	T	174	14	8,05
		Merged		
		All	Correct	Correct%
6	Q	231	134	58,01
6	T	698	538	77,08
17	Q	231	138	59,74
17	T	698	542	77,65

Table 4 Results of the model for W and E sector block

Principal components	Evaluation data	All states		
		All	Correct	Correct%
5	Q	42	34	80,95
5	T	132	130	98,48
17	Q	42	40	95,24
17	T	132	129	97,73
		Split		
		All	Correct	Correct%
5	Q	24	22	91,67
5	T	77	77	100
17	Q	24	24	100
17	T	77	77	100
		Armed		
		All	Correct	Correct%
5	Q	12	8	66,67
5	T	38	36	94,74
17	Q	12	11	91,67
17	T	38	35	92,11
		Merged		
		All	Correct	Correct%
5	Q	6	4	66,67
5	T	17	17	100
17	Q	6	5	83,33
17	T	17	17	100

Another reason of the low accuracy can be the fact that we did not distinguish between sector blocks in the model and looked upon them as one common group using only one type of network to provide results for all of them. We did not take into consideration that the structure of sector blocks can largely differ from each other (e.g. some blocks are made up of only two basic sectors while others include five). To examine the effect of using a smaller, more homogeneous set of sector blocks to the results of the model, we performed our calculations again using only the data related to the W and E sector blocks. The results obtained are given in Table 4.

Table 4 shows that by narrowing the set, accuracy increased greatly which means that using smaller groups of sector blocks can be a possible way of getting better results with the same model. On the other hand it is worth mentioning that in an ideal case, such models would need to handle problems generated by the different size and shape of sectors on their own. The model parameterized by the method does not utilize the proper amount or type of data to describe complexity of sector structure. This is an issue that is going to be worked on in the future.

7 Conclusion

Based on the results shown is Section 6, we can say that using a neural network model for the estimation of airspace capacity seems to be a suitable solution. This is especially true if we consider the fact that the present research is a preliminary study and it is not aimed at the development of a model to be implemented in real air traffic control systems. The latter would require a much greater amount of data for both parameterization and validation. This makes it reasonable to improve the methods we used by either modifying parameters (e.g. by using more complexity factors that describe sector structure) and/or by using more sophisticated software to implement the neural network logic. In short-terms, our current parameters and software can be satisfied too, if we make our neural network calculations on smaller sets of sector blocks. This solution however could not be adapted to a possible change in the sector structure of Hungarian airspace. Besides the above, it could also be considered to try and apply other types of airspace capacity estimation models (like those described briefly in Section 2) to the airspace of Hungary.

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