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UTILISATION OF THE ARTIFICIAL NEURAL NETWORK IN THE STRATEGY FOR THE ALLOCATION OF STORAGE SPACE

Piotr JANKE[1*], Paweł JOŃCZYK[2]

[1] Silesian University of Technology, Faculty of Organization and Management; piotr.janke@polsl.pl, ORCID: 0000-0001-8065-9013
[2] jonczykpawel@yahoo.com
* Correspondence author

Purpose: The main goal of the article is to develop a method that automatically allocates the warehouse zones of the product range of the studied enterprise for the selected machine learning algorithm.
Design/methodology/approach: The problem of the studied issue is presented in the context of a specific company. The research used the double ABC method for the initial classification of zones. Input data were prepared according to the developed methodology. Selected machine learning algorithms were tested for the same data.
Findings: Machine learning methods can be used to classify storage zones in that specific warehouse. Especially Boosted Trees and Neural Networks gives small errors at training stage witch our methodology. There may be differences in errors at the stage of learning the algorithm and the stage of implementing it with completely new data.
Originality/value: Machine learning is a new solution that is increasingly used in various areas of logistics. The article draws attention to some problems in implementing this solution for enterprises.

Keywords: Logistics, Machine learning, Artificial intelligence, Neural networks.

Category of the paper: Research paper, Case study.

1. Introduction

One of key factors influencing the operation of the entire warehouse is the proper distribution of goods in storage areas. With an appropriate allocation strategy, the time for completing shipments can be significantly shortened, which is of major importance in the rapid execution of customer orders, and is particularly significant in today's competitive market.

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Taking into account the number of criteria (Krzyżaniak, and Niemczyk, 2013) that determine where a given shipment is to be placed, it is possible to distinguish between single-criterion and multi-criteria methods, which also include the application of artificial intelligence algorithms presented later in the article.

Among single-criterion methods of distribution of goods to fixed storage areas may be distinguished (Lorenc, 2014):

- ABC method,
- XYZ method.

Among the multi-criteria methods and techniques of product allocation can be distinguished:

- COI index,
- EIQ analysis.

The ABC method is based on the division of stocks into three groups, assuming that these are divided into those which quantitatively account for a large percentage of stocks in general but represent a small value, and vice versa. Therefore, it is possible to distinguish (Bril, 2013):

- Group A — stocks which have the largest share in the total value, but quantitatively constitute 5-20% of the total stock,
- Group B — stocks constituting 15-20% of both value and quantity,
- Group C — stocks constituting the largest group in terms of quantity, amounting to 60-80%, while representing a small value of about 5%.

The XYZ method is a variation of the ABC method. The application of this method assumes the division of stocks into three groups based on the regularity of demand. Therefore, it is possible to distinguish (Bril, 2013):

- Group X — stocks with a regular demand and high accuracy of forecasting this demand,
- Group Y — stocks with a specific demand trend such as seasonal fluctuations and average forecasting accuracy,
- Z Group — stocks with irregular demand and low accuracy of forecasts.

In practice, XYZ analysis is most often combined with ABC analysis, since used solely as a tool, it does not give the expected result (Lorenc, 2014, p. 3832).

The COI is a two-criteria analysis taking into account two factors: the size of the product expressed in its cubic capacity, or weight, and the demand reflected in the number of product intakes or average demand (Lorenc, 2014).

The application of this method allows the allocation of products in such a way as to shorten the route covered by the largest or heaviest goods, that is, with the lowest COI (Lorenc, 2014, p. 3833).

The EIQ analysis is a method which, apart from the most frequently used criterion, which is the quantity and type of stock, takes into account the third factor, that is the order list (Li, 2009).

This method uses combinations of the previously mentioned factors (Lorenc, 2014, p. 3834):

- EQ — volume of orders (Q) of individual customers (E),
- EN — number of product types (N) ordered by customers (E),
- IQ — order size (Q) for product type (I),
- IK — order frequency (K) for individual product types (I).

This analysis divides the groups into three groups A, B and C and provides results for each criterion separately, so that a single criterion or a combination of several criteria can be taken into account for the final allocation of goods.

The aim of the article is to develop a method for automatically allocating storage areas of the assortment of the examined company.

2. Methodology

In the presented article, the authors will try to teach the previously developed neural network the correct allocation of storage areas based on previously prepared input data. The task of the neural network will be to correctly allocate the storage area for specific items of assortment with a particular demand and weight.

The first stage of the research includes preparing the input data, determining the desired storage areas and creating models of machine learning algorithms.

The second stage of research includes the evaluation of the models built and the implementation of artificial neural networks for determining storage areas.

2.1. Data set

The researched company produces low and medium voltage cables and wires. It is an international company with two manufacturing plants and warehouses in Poland.

The following figure 1 shows a map of the warehouse with the layout of individual storage areas. Each storage area has in-row racks with aisles.

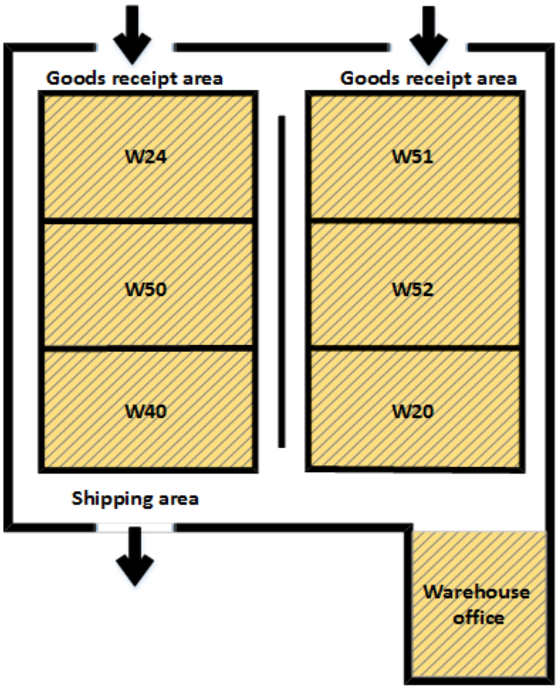

Figure 1. A map of the warehouse of the company with a division into storage areas. Adapted from: Own elaboration based on data provided by the researched company.

Goods are accepted into the warehouse from production through the receipt area and are transferred to storage areas located in the designated zones on the basis of the system indications. Once the delivery is established, the goods are taken from the indicated zones and then released from the warehouse through the shipping area.

To conduct the research, data on transfer orders from one month were collected. This data is called a 'learning set' and it contains information (attributes) about what kind of goods were released from the warehouse, from which zone they were released, what was the weight of the goods on the pallet and what was the demand for a given goods in the analysed period. This information is necessary in order to teach the neural network to allocate storage areas according to the weight of goods on the pallet and demand, so that the fastest moving and heaviest goods are as close as possible to the shipping area in order to shorten picking time. This information is then an input variable, that is, an order to teach our algorithm to allocate zones correctly. The input file developed in this way contains 778 cases, or transfer orders. Additional information entered in each item is the desired storage zone – the zone in which the goods should ideally be stored. This information is an output variable. It is determined by a double ABC analysis, which gives similar effects as the use of the COI index, but is quicker to apply in case of a small quantity of goods.

Material	Area	Demand	Weight [kg]	Proposed area
13025013	W20	0,15	708	W40
13025013	W20	0,15	708	W40
13025013	W20	0,15	708	W40
13025013	W20	0,15	708	W40
13025013	W20	0,15	708	W40
13025013	W20	0,15	708	W40
13025013	W20	0,15	708	W40
13025013	W20	0,15	708	W40
13025013	W20	0,15	708	W40
13025015	W24	0,26	612	W20
13025015	W24	0,26	612	W20
13025015	W24	0,26	612	W20
13025015	W24	0,26	612	W20
13025013	W24	0,15	708	
13025013	W24	0,15	708	
13025013	W20	0,15	708	
13025013	W24	0,15	708	
13025013	W20	0,15	708	
13025013	W24	0,15	708	
13025013	W20	0,15	708	
13025013	W24	0,15	708	
13025013	W20	0,15	708	
13025013	W24	0,15	708	
13025013	W20	0,15	708	

Train data

Model creation

Test data

Figure 2. Fragment of the prepared data. Adapted from: Own elaboration.

The table shows the data structure proposed and used later in the research. The data set was classically divided into train and test data in the proportions of 2/3 to 1/3. Particularly, the aim of the study is to teach the selected model of allocating storage zones independently, without the need to use this method for each assortment item.

2.2. Methods

Machine learning is a field within the canon of artificial intelligence science. A learning program can be illustrated as a program that uses a parametrised, abstract algorithm to perform a task. Learning in such a case involves selecting appropriate parameters based on historical data, in order to transform an abstract algorithm into a specific one that meets the designer's requirements (Cichosz, 2000).

The neural network is a much simplified model of the brain. This network consists of a large number of information processing elements, ranging from several hundred to tens of thousands. These elements are called neurons, even though their functions are very simplified compared to real neural cells. Neurons bind together to form a network using connections of parameters called weights, which are modified during a process called learning. The topology of learning, as well as their parameters, form the program of the network, while the signals appearing at its outputs responding to specific input signals are the solutions to the tasks that are set before it.

The majority of modern neural networks developed and used nowadays have a layered structure, and taking into account the availability during the learning process, the input, output and so-called hidden layers can be distinguished (Tadeusiewicz, 1993) Neurons create connections between successive layers, in the so-called neighborhood or group or between any layers. The way the signal passes through such structures is closely related to the way of distribution and the method of connection of neurons, as well as number. The system of these connections may have one direction, in this case, the signal flows from the input through the layer of hidden neurons to the output, that is, only in one direction or may have feedback (recursive system). Due to the feedback, the network has return connections between later and earlier neurons (Duch et al., 2000). Depending on how the neurons are distributed in the artificial neural network, an appropriate method of its learning is selected, which aims at the appropriate selection of weights, that is, numerical values. The interpretation of weights depends on the type of network, as well as the optimisation of network performance in solving a specific task. Słowiński (Słowiński, 2009) presents two ways of teaching the network — under supervision, and also without supervision. After teaching the neural network, its quality of learning, learning error, validation quality and test error is checked. The most essential information that is taken into account in the evaluation and subsequent selection of the neural network is the value of validation error.

Boosted trees is a method that consists of building a sequence of models. Each subsequent model attaches greater importance to observations that have been incorrectly classified by previous models. In subsequent models, incorrectly classified observations are given greater weight, so that each subsequent model learns better to distinguish observations that were previously misclassified. A finished model often consists of several hundred component models, which by voting give the final result.

An unquestionable advantage of boosted trees is that they do not require such involvement of analysts in the data cleaning process. Clearly, they handle both qualitative and quantitative data, and are insensitive to outliers and rare classes. Another advantage of this method is its resistance to the occurrence of meaningless data as well as excessively correlated characteristics. Therefore, when building a model using this method, a number of time-consuming and labour-intensive stages of data analysis are eliminated, but on the other hand, there is also a risk that noises and errors contained in the data (which were not identified at the cleaning stage) will cause the model to generate not proper results. This method is also relatively resistant to the occurrence of unbalanced proportions of good and bad cases in the data set, as opposed to other methods, such as neural networks (Migut, 2010).

CART is regarded as the most advanced algorithm for building decision tree models (Breiman, 1984). Both the dependent and independent variables may be at any level of measurement, while the analysis itself does not require any assumptions.

The characteristics of the CART algorithm are:

- It does not require transformation of variables (e.g. extraction of a root, logarithming).
- Automatically selects the best predictors (building hierarchy of independent variables).
- Automatically discovers the effects of interaction.
- It is resistant to abnormal observations.
- Only moderate supervision is required from the researcher during model development.
- It does not require replacement of data gaps.

The CART algorithm can recognise the data structure, but in the case of a very complex tree model it does not guarantee a clear presentation of the model. Moreover, it also happens that a tree made of a large number of leaf nodes presents a very simple relationship between variables.

The SVM algorithm can be applied for both regression and classification. The SVM algorithm converts the original space in which the classification problem was defined into a space with more dimensions. By performing the transformation in such a way, after it is done, in the new space, objects can be separated by a hyperplane (such separation is usually impossible to perform in the original space). The main stage of the transformation is the selection of the kernel function, which is responsible for mapping individual points into the new space. Taking into account regression, the SVM algorithm finds a continuous function in the newly created space, in the closest vicinity of which the largest number of objects is located. In order to achieve the expected results, the SVM algorithm needs careful selection of the kernel function and its parameters. As experience proves, these algorithms give very good results in practical applications, such as: biomedical data analysis, text and image classification, handwriting recognition. Owing to a special version of the algorithm, called one-class SVM, the SVM algorithm can also be used to detect outliers (Morzy, 2013).

A random forest is a set of classifiers, in which each classifier is a learning decision tree until only samples from the same class are in the leaf (Breiman, 2001). Classifiers belonging to a random forest are taught on a specially drawn data sample, created by drawing n times with the return of all the N-templates. This technique, which involves generating data is called bagging or bootstrap aggregating. Moreover, when building the decision tree, not all attributes are taken into account when determining the decision rule in the node. Instead, the attributes that are the basis for the decision rule in the node are drawn. This method is called feature subspace. Both of these techniques — bagging and feature subspace — are used to increase the stability of the algorithm's response and protection against over-matching to the train data. When predicting a class for a sample, it is shown to all decision trees, and the most often indicated class affiliation is treated as the final decision. The advantage of a random forest is that each tree can be determined independently, so that the calculations required to determine the entire forest can be performed in parallel. Another advantage is that the algorithm is able to determine the validity of the input attributes. A random forest demonstrates better stability of operation and usually gives better classification results when compared to a single tree, however, at the same time the simplicity of interpretation of the classifier operation is lost (Płoński, Zaremba, 2014).

3. Results

For the purpose of creating machine learning algorithm models, input and output variables were selected. As an output variable, the proposed zone was chosen because the task of the algorithm is to classify, that is, to assign the appropriate zone (label) based on the input data.

Table 1.
Proposed variables used in the research

	Variable name	Role	Type
	Material	Input	Continuous
	Area	Input	Categorical
	Demand	Input	Continuous
	Weight [kg]	Input	Continuous
	Proposed area	Target	Categorical
Number of cases after data definition step	778		

Adapted from: own elaboration.

As shown in the table, four variables were used as input. Three of them are data of categorical type and one variable of continuous type. The variable is explained by the categorical type. From the train and test data and algorithm settings, machine learning algorithm models were created. The following table shows the training error of each model. It can be seen that the created neural network algorithm shows a low training error compared to four other selected algorithms. Only the boosted tree algorithm performed slightly better at the model building stage.

Table 2.
Training error for individual algorithms

Model ID	Name	Training error (%)
3	Boosted trees	1,41
5	Neural network	1,67
1	C&RT	2,31
4	SVM	4,76
2	Random forest	18,64

Adapted from: own elaboration.

The quality of the created models can also be presented on growth charts. A good model is characterised by a line that descends slightly downwards as the percentile grows.

To illustrate the situation properly, one of the zones with a large number of matches was selected. It can be seen that all algorithms are characterised by a high incremental value for a small number of percentiles, and then decrease until they finally reach lift value of 1.

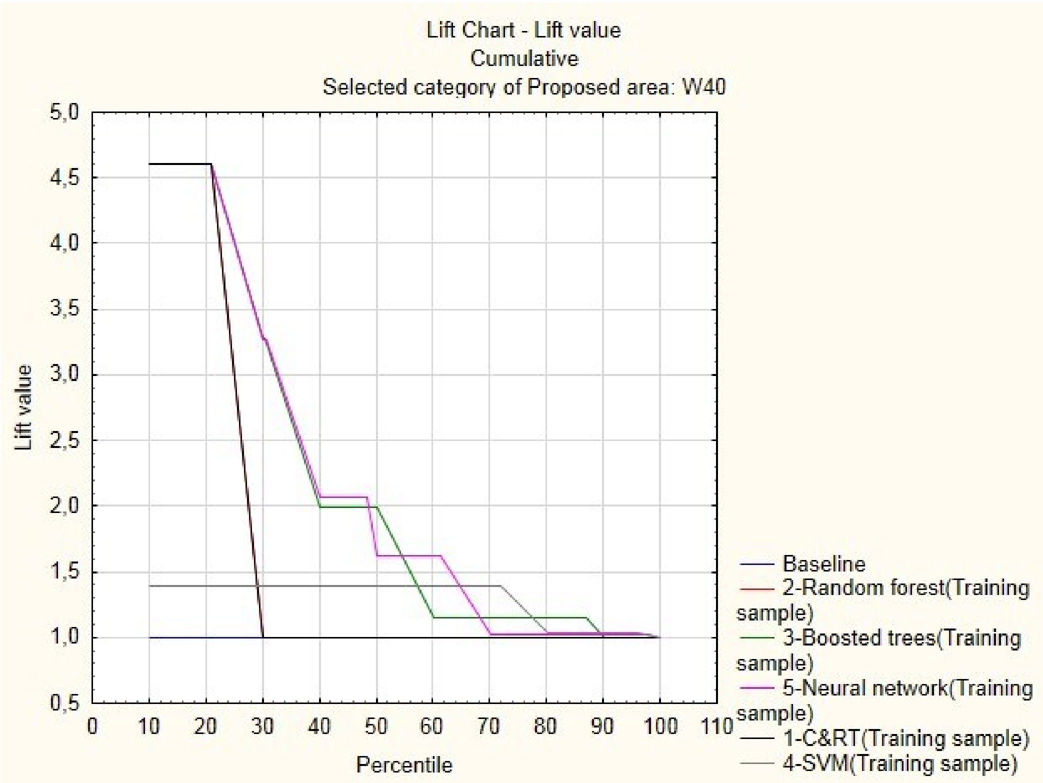

Figure 3. Growth chart for one of the zones. Adapted from: TIBCO Software Inc.

For further analysis, due to later implementations, an artificial neural network was selected with a training error at the stage of model creation of 1.67. Below, the matches to subsequent storage areas at the stage of model creation are presented.

Table 3.
Prediction of the artificial neural network in individual zones at the model creation stage

	Proposed area	Neural network Prediction W40	Neural network Prediction W20	Neural network Prediction W50	Neural network Prediction W24	Row
Count	W40	163	0	6	0	169
Column Percent		100,00%	0,00%	1,12%	0,00%	
Row Percent		96,45%	0,00%	3,55%	0,00%	
Total Percent		20,95%	0,00%	0,77%	0,00%	21,72%
Count	W20	0	31	0	0	31

Cont. table 3.

Column Percent		0,00%	81,58%	0,00%	0,00%	
Row Percent		0,00%	100,00%	0,00%	0,00%	
Total Percent		0,00%	3,98%	0,00%	0,00%	3,98%
Count	W50	0	0	530	0	530
Column Percent		0,00%	0,00%	98,88%	0,00%	
Row Percent		0,00%	0,00%	100,00%	0,00%	
Total Percent		0,00%	0,00%	68,12%	0,00%	68,12%
Count	W24	0	4	0	0	4
Column Percent		0,00%	10,53%	0,00%	0,00%	
Row Percent		0,00%	100,00%	0,00%	0,00%	
Total Percent		0,00%	0,51%	0,00%	0,00%	0,51%
Count	W51	0	3	0	0	3
Column Percent		0,00%	7,89%	0,00%	0,00%	
Row Percent		0,00%	100,00%	0,00%	0,00%	
Total Percent		0,00%	0,39%	0,00%	0,00%	0,39%
Count	W52	0	0	0	41	41
Column Percent		0,00%	0,00%	0,00%	100,00%	
Row Percent		0,00%	0,00%	0,00%	100,00%	
Total Percent		0,00%	0,00%	0,00%	5,27%	5,27%
Count	All Grps	163	38	536	41	778
Total Percent		20,95%	4,88%	68,89%	5,27%	

Adapted from: own elaboration.

The final and most essential step was to check the selected and learnt algorithm on data not used for model training. The neural network algorithm with experimentally selected parameters was chosen for implementation. The algorithm allocated storage areas, but the percentage of mismatches at the implementation stage was as high as 30%. As can be observed, many areas were allocated incorrectly.

Table 4.
Storage area allocation – selected fragment with wrong classifications

Proposed area	Neural network Prediction	Neural network Residual
W20	W20	Correct
W20	W20	Correct
W20	W20	Correct

Cont. table 4.

W52	W20	Incorrect
W52	W20	Incorrect
W20	W50	Incorrect
W40	W40	Correct
W20	W50	Incorrect
W20	W50	Incorrect
W50	W50	Correct

Adapted from: own elaboration.

The artificial neural network misclassified areas many times. The low training error in the allocation of storage areas did not result in a sufficiently low test error at the implementation stage as expected. The built model needs to be further reworked.

4. Discussion and related work

The analysis conducted showed that neural network algorithms can be used to allocate storage areas. It is necessary to prepare the data properly, so that the algorithm is able to allocate appropriate storage areas based on the input data. Due to the double ABC analysis, it has become feasible to take into account the criteria of interest based on which the goods were allocated (e.g. weight and frequency of picking, demand for a given goods).

The main reason why the test error in the analysis is much higher than the training error may be due to the fact that the algorithm received data for analysis that it had not analysed before. This was not the same data as at the model creation stage, so the number of mismatches was higher.

A further possible reason for the high percentage of mismatches may be that the algorithm is overmatched with the train data. This is indicated by low error rates at the training stage and high error rates at the test stage. In order to reduce the effect of overtraining, it is possible to use cross-validation at the modeling stage or use the early stopping method. Cross-validation involves creating a series of training and test sets based on the division of a single data set. Early stopping is the end of the model training stage when the validation error stops decreasing.

5. Conclusion

In order to create a model of an artificial neural network, data on releases of goods from storage areas were used, called transfer orders. These data came from a period of one month. The amount of data used proved to be sufficient to create the model. The previously prepared data were divided in the ratio of 2/3 and 1/3. The first part served as train data to create models of machine learning algorithms, the second part was used as test data to evaluate the implementation of the selected neural network model.

For the artificial neural network algorithm to allocate storage areas based on two factors, i.e. the weight and frequency of pickings of the assortments, it was decided to apply a double ABC analysis. This allowed to determine the proposed storage areas which were used to create the model.

The created neural network model is subject to a high test error, which may be due to the algorithm being overly matched to train data. It is therefore possible to use cross-validation or early stopping to reduce the above-mentioned overmatching and, eventually, a more effective neural network model. The next step in the development of a method using neural networks for the allocation of storage areas will be to apply these methods, as well as other parameters that have an impact on the effects of neural networks.

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