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EXPERT SYSTEM MODELS FOR FORECASTING FORKLIFTS ENGAGEMENT IN A WAREHOUSE LOADING OPERATION: A CASE STUDY

ABSTRACT

The paper focuses on the problem of forklifts engagement in warehouse loading operations. Two expert system (ES) models are created using several machine learning (ML) models. Models try to mimic expert decisions while determining the forklifts engagement in the loading operation. Different ML models are evaluated and adaptive neuro fuzzy inference system (ANFIS) and classification and regression trees (CART) are chosen as the ones which have shown best results for the research purpose. As a case study, a central warehouse of a beverage company was used. In a beverage distribution chain, the proper engagement of forklifts in a loading operation is crucial for maintaining the defined customer service level. The created ES models represent a new approach for the rationalization of the forklifts usage, particularly for solving the problem of the forklifts engagement in cargo loading. They are simple, easy to understand, reliable, and practically applicable tool for deciding on the engagement of the forklifts in a loading operation.

KEY WORDS

forklifts; loading operation; expert systems; machine learning; ANFIS; CART tree;

1. INTRODUCTION

Warehouses are an essential part of most supply chains and they have to contribute to the logistics strategy [1]. Usually, they occur as a weak spot of the entire supply chain; to avoid this phenomenon, special attention should be paid to the optimization of warehouse operations [2]. Warehouse operations are various and complex and forklifts have a crucial role in them. McGillivray and Saipe [3] (cited in [1]) found that forklifts were by far the most widely used equipment for moving materials from warehouses, being used by 94% of companies. Proper engagement of forklifts in the loading operation directly influences the high level of probability of on-time delivery, resulting in a direct impact on the customer service level [2]. Besides the influence on service level, the engagement of forklifts also impacts the productivity of other factory activities – the number of forklifts deployed in the cargo loading directly influences the number of remaining forklifts which can be deployed in other factory activities. In practice, decisions regarding forklifts engagement are left to the warehouse experts.

In this paper, the case study is carried out on the central warehouse of the beverage factory, which has 30 forklifts, engaged in various operations inside the factory complex, and not being deployed only in the warehouse sector. The central warehouse has the capacity of 11,100 pallet places and the annual output from 300,000 to 350,000 pallets (depending on the varying customer demands). Currently, the factory is supplying around 20,000 supermarkets via direct delivery. In the particular company, the expert decisions regarding forklifts engagement are based on their experience, without the help of any decision-support system (DSS). There is a substantial amount of empirical evidence that human intuitive judgment and decision-making can be far from optimal, and it can deteriorate even further with complexity and stress [4]. That is one of the main reasons why experts should have some DSS as a support tool in the decision making process. According to Turban [5], expert systems (ES), as part of DSS, are ideal for assistance in this kind of decision-making.

There is a lack of models in literature dealing with forklifts engagement in a loading operation. Mircetic, Lalwani [6] proposed using the adaptive neuro fuzzy inference system (ANFIS) for making decisions regarding forklifts engagement in a loading zone. Also, to our best knowledge, there is no proposed methodology in literature dealing with building the ES for forklifts engagement in a loading operation. For the purpose of this research, we adopted the general methodology steps for creating ES, proposed by [7, 8], which will be presented in Section 3. Bearing in mind that the efficiency of the loading operation influences the efficiency of the given distribution chain, and that forklifts directly affect the efficiency of a loading operation, this paper deals with the development of the forward chaining rule-based ES models for engaging forklifts in a loading operation. Two ES models are created, complementary to each other. The first model deals with determining the number of forklifts that need to be engaged in a loading zone (ES model 1). The second one deals with the problem of determining which forklifts should be engaged (ES model 2). The models are created using supervised machine learning (ML) techniques. According to Turban, Aronson [8], ML has shown very good results in designing the intelligent DSS. In this research, several ML techniques have been used, and some among them are seen as the state-of-the-art techniques, such as: ANFIS, generalized additive models (GAM), Random forests, Boosting, etc. [9]. The created models have been interchangeably compared, and as best models in the given problem, ANFIS and classification and regression trees (CART) have emerged.

The remainder of this paper is organized as follows: next section gives theoretical background and the problem description, with the focus on describing the manager's decision-making process while engaging forklifts on a loading operation. In Section 3, methodology steps for building ES and elementary principles of ANFIS and CART are provided. Sections 4 and 5 present the core of the paper. Section 4 includes the development of two ES models for engaging forklifts in a loading operation. In Section 5, the evaluation of ESs is performed by comparing several ML techniques on a given problem. Section 6 represents a discussion on model outputs, their practical applications and limitations. Section 7 provides final remarks and highlights scientific and practical contributions for further optimization of warehouse operations.

2. THEORETICAL BACKGROUND AND PROBLEM DESCRIPTION

DSS could be characterized as a computer-based information system that combines models and data in an attempt to solve semi-structured and unstructured problems with the extensive user involvement [7]. According to Marakas [10], DSS is a system under the control of one or more decision makers that assists in the activity of decision making by providing an organized set of tools intended to impose a structure on portions of the decision-making situation and to improve the ultimate effectiveness of the decision outcome. Benefits of DSS in logistics are presented in a series of studies that emphasize the increase in the productivity or better organization of the logistics system after the implementation of DSS [7, 10-15]. Proper application of DSS increases productivity, efficiency, and effectiveness, and provides many businesses with a comparative advantage over their competitors, allowing them to make optimal choices for technological processes and their parameters, planning business operations, logistics, or investments [4]. According to Turban [5], ESs are considered to be part of DSS. Olson and Courtney [16] define ES as a computer program within a specific domain, involving a certain amount of artificial intelligence to emulate human thinking in order to arrive to the same conclusions as a human expert would. An ES component is ideal to assist a decision maker in an area where expertise is required [17]. Essentially, an ES transfers expertise from an expert (or other source) to the computer [7]. It can either support decision makers or completely replace them, and it is most widely applied and commercially successful artificial intelligence technology [7]. One of the justifications for building an ES is to provide expert knowledge to a large number of users [18]. This is exactly the case in the observed company, since the manager will be frequently absent in the near future. Consequently, novice managers with less experience will need help and guidelines of ES when making decisions regarding forklifts engagement.

During the shipment of products, the warehouse expert determines how many forklifts and which of them will be deployed in loading. Manager's decisions are conditioned by three issues: (1) loading must be finished within a defined time, (2) other activities that require forklifts should be disturbed as little as possible, and (3) utilization of forklifts should be in accordance with the possibilities of performing the overhaul in the workshop. The workshop can simultaneously perform the overhaul on only two forklifts. By average, each forklift has four to five maintenance overhauls in one year (three to four small and one large overhaul).

For the loading operation, forklifts are crucial, and despite difficult operating conditions, loading operations have to support a defined marketing strategy. However, an expert also needs to ensure normal functioning of other activities requiring forklifts. A common problem occurring with deploying the remaining forklifts to other operations results from the fact that this number is directly affected by the number of forklifts already deployed in the loading of finished products. If the number of forklifts deployed on loading is higher than the actual demand, then the expenses occur due to the inadequate utilization of company resources and the delay occurs in the execution of other activities. On the other hand, if an expert engages a smaller number of forklifts than the actual demand, the company's reputation and service level will decrease. Furthermore, if time for loading is exceeded, the company is obliged to pay the penalty for the delay in delivery. Also, the manager needs to combine forklifts through all activities in the factory complex to avoid the situation that more than two forklifts need to be overhauled at the same time, and that some forklifts usually need to be overhauled more than the others. The already mentioned manager's decisions are in most cases right; however, in situations where there is great noise, stress, and where decisions are made often and fast, even the experienced manager can make wrong decisions. Therefore, a manager needs the assistance of ES to obtain greater confidence and reliability during decision making.

3. METHODOLOGY APPROACH

In order to transfer expertise from an expert to a computer and then to the user, several steps are proposed in [7, 8]. For the purpose of this research, the proposed steps are adopted and adjusted, adding one additional step in methodology (Evaluation of knowledge inferencing models), *Figure 1*. Following the presented steps, two ES models are created.

The knowledge acquisition was obtained from interviewing a manager, following his decision-making process and searching through the warehouse record keeping. In order to create ES in a given problem, two knowledge bases were formed. The first base contains decisions regarding how many forklifts were engaged in the loading zone (434 expert decisions), while the second contains which forklifts were engaged (368 expert decisions), in different operation situations. In the knowledge inferencing step, several ML techniques were applied, using Matlab software. Apart from the techniques mentioned in Section 1, the following ones were also used: Extended linear regression, Logistic regression, k-Nearest Neighbors (KNN), Linear discriminant analysis (LDA) and CART. Accordingly, different ML models were evaluated, and models with best performances were identified. For a given problem, ANFIS and CART showed best results, and therefore they were chosen as final ESs for practical application in the observed company. Knowledge transfer was obtained through the user interface of final ES models. The structure and logic of ESs is shown in *Figure 2*. Since ANFIS and CART models have shown the best knowledge inferencing and transferring properties, their theoretical foundations are briefly discussed in the next two subsections.

The factors that influence the manager's decisions are determined in consultation with the manager, and,

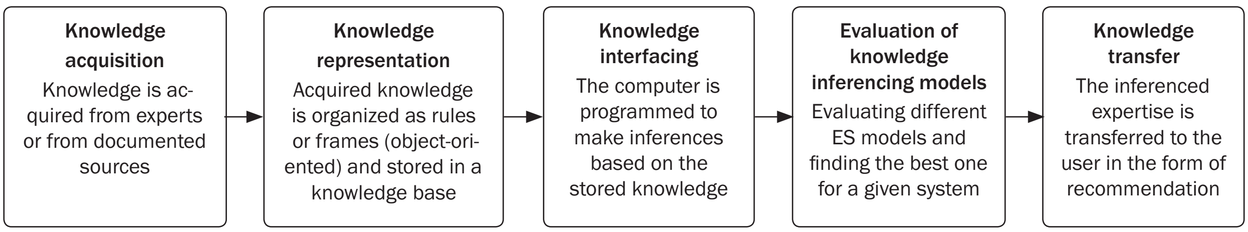

Figure 1 – Methodology steps for building ES, Source: adapted from [7, 8]

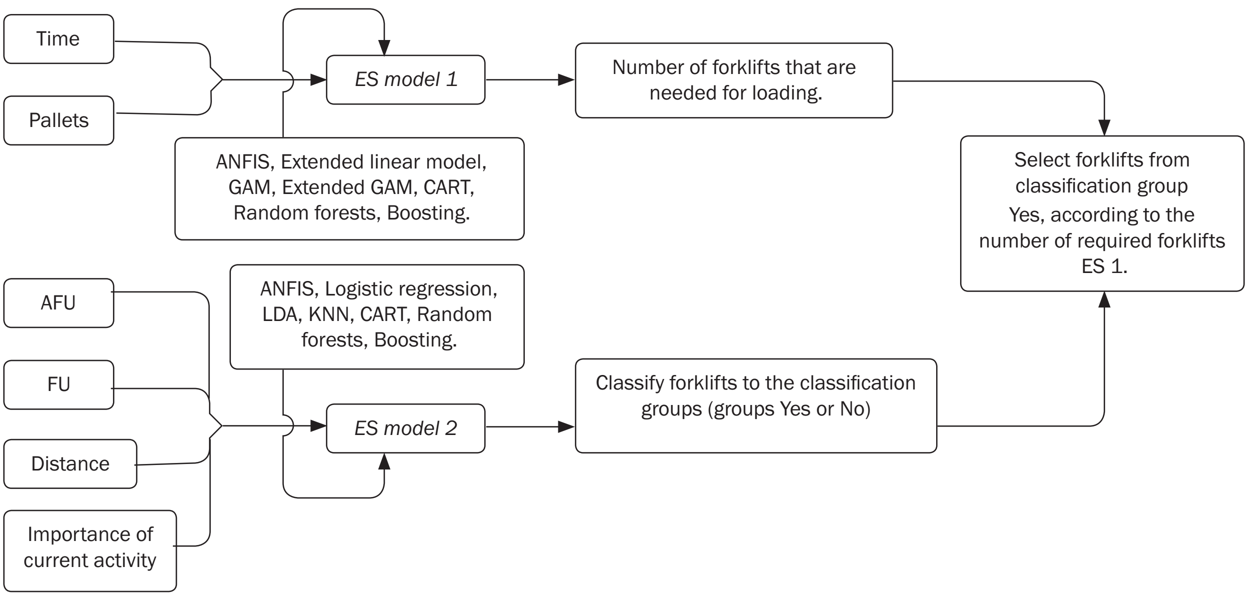

Figure 2 – Building structure of ESs

for deciding how many forklifts to deploy in the loading zone, they are the following: specified loading time and the amount of cargo to be loaded. For the first input variable – time (specified loading time), the observed interval is from 15 to 135 minutes, while for the second variable – pallets (amount of cargo), the interval is from 15 to 225 pallets. The numbers are obtained from the fact that these are the most common intervals to finish loading and the most common amounts of the cargo to be loaded. Further, when deciding which forklifts to engage on loading, the manager is guided by the following several factors: importance of the activity that a forklift is currently doing, utilization of forklift, current distance from the loading dock, and the average utilization of all forklifts. The importance of activities ranges from 1 to 9, and it is defined by the company's policy rules. For forklifts in a given company, the scale is organized in the following manner: 9 – assistance in full production activities, 8 – assistance in semi-production activities, 7 – commissioning the shipments, 6 – loading/unloading, 5 – position rearrangement of products in the warehouse, 4 – other activities in the main central warehouse, 3 – disposal of returned products from the market, 2 – working in the warehouse of commercial and raw materials, 1 – other activities. Each forklift has a defined amount of working hours until the next overhaul. The usage of a forklift is not allowed after this time is exceeded. Forklift utilization (FU) is the percentage of working hours spent by the observed forklift to the present moment. Average forklift utilization (AFU) is the average amount of working hours spent in the utilization of all forklifts. The higher the AFU value, the greater is the chance that the majority of forklifts will soon utilize all of their allowed working hours and will need overhaul.

3.1 ANFIS model

When defining the fuzzy inference system (FIS), there are two approaches. The first approach is based on the expert estimation of the relation between different variables, while the second one consists of determining the relations between the input and output values, based on data collected by observing a certain phenomenon being modelled. Historically, fuzzy systems grew out from the context of human machine interface. Older identification algorithms had, therefore, quite modest approximation properties compared to the methods developed more recently [19]. An important step towards new methods in fuzzy modelling is the introduction of Takagi & Sugeno inference system, together with the method of the least squares for consequences parameter identification [20]. Takagi & Sugeno inference system is the most frequently used form of FIS in the ANFIS structure. ANFIS structure with Takagi & Sugeno inference was first presented by Jang [21], and it represents a combination of neural networks and fuzzy logic. In ES literature, this combination is known as the fuzzy neural networks [8]. According to Liao [22], the combination of neural network and fuzzy logic are among the widely used ES methodologies, with a variety of implementation areas; in literature, they are highlighted as great tools for mapping the human knowledge in numerical values [21, 23-26].

3.2 CART model

The tree-based method partitions the feature space into a set of rectangles and then fits a simple model (like a constant) in each one. They are composed of nodes denoting goals and links representing decisions [8], and they are conceptually a simple yet powerful method [9]. CART is a popular non-parametric method for the tree-based regression and classification, developed by [27]. Since CART is a non-parametric method, no assumptions are made regarding the underlying distribution of values of the predictor variables. Thus, CART can handle numerical data that are highly skewed or multi-modal, as well as categorical predictors with either ordinal or non-ordinal structure. Another great advantage of the CART trees is that they are relatively simple for non-statisticians to interpret [28], which is very important in the areas of application where the end users are not trained in statistics and mathematics. The classification of CART trees has a basic task of classifying values into discrete categories (classes).

4. ES CHARACTERISTICS

4.1 ES Model 1 – ANFIS

Steps used for building the ANFIS model are shown in *Figure 3*. The performance of the created ANFIS model is directly dependent on the parameters selected in the second step of the diagram (Generate FIS). In a given problem, the Gaussian types of the membership functions produce the best results. Each input variable is assigned with three membership functions (small, medium, and large). First order polynomials are chosen to represent each output rule. For forming the rule base, the grid partition is chosen, and the model is trained with a hybrid optimization algorithm (least squares & gradient descent), up to 2,000 epochs. As a result, a neural network with 9 inference rules is created.

For training the neural network, 300 training observations are used. This means that, for the model with two input variables, the total number of data points for fitting a single input is 17.3 since $\sqrt{300} = 17.3$. According to Jang, Sun [29], this is a sufficient amount of data for ANFIS to perform system mapping. The total number of parameters in the neural network

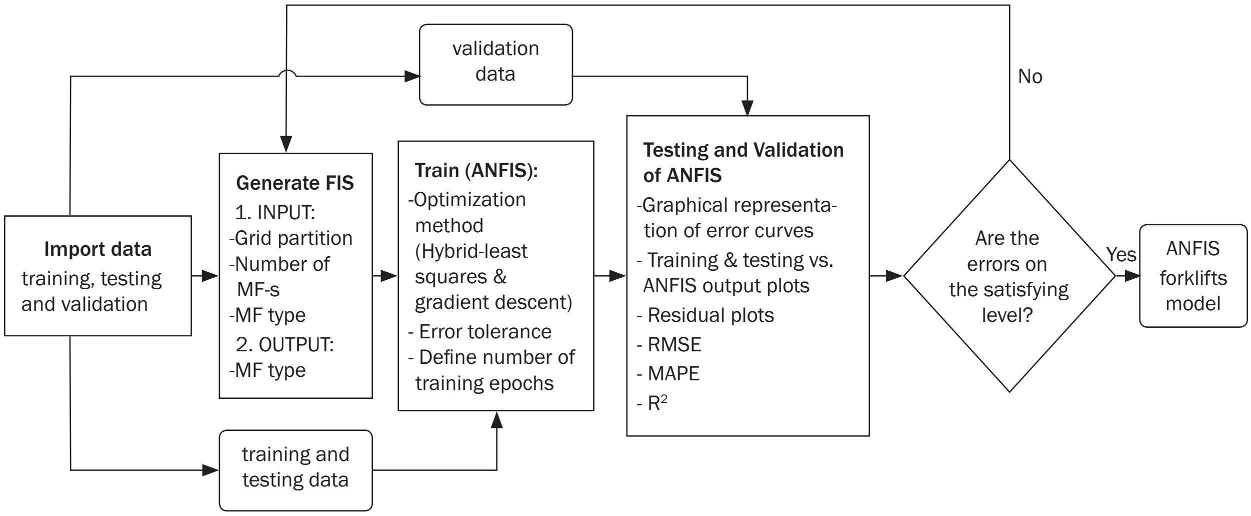

Figure 3 – Methodology steps for building the ANFIS model

Table 1 – FIS elements of the ANFIS model

Input variables		Rule	IF (Time is $\mu_i(t)$) & IF (Pallets are $\mu_i(p)$) THEN Rule		
Time $\mu_i(t)$	Pallets $\mu_i(p)$		IF		THEN
			Time	Pallets	Rule (f_r)^a
		1	small	small	f_1=-0.15x+0.12y-3.6
$\mu_s(t) = e^{\frac{-(x-7.77)^2}{2\cdot(95.34)^2}}$	$\mu_s(p) = e^{\frac{-(y-16.16)^2}{2\cdot(68.63)^2}}$	2	small	medium	f_2=-1.28x+0.12y-8.5
		3	small	large	f_3=-0.98x+0.12y-6.29
		4	medium	small	f_4=-0.1x-0.04y+23.71
$\mu_m(t) = e^{\frac{-(x-130.5)^2}{2\cdot(75.14)^2}}$	$\mu_m(p) = e^{\frac{-(y-156.7)^2}{2\cdot(62.7)^2}}$	5	medium	medium	f_5=-0.4x-0.04y+131.3
		6	medium	large	f_6=-0.23x-0.05y+96.61
		7	large	small	f_7=-0.05x-0.02y+18.35
$\mu_l(t) = e^{\frac{-(x-295.2)^2}{2\cdot(72.94)^2}}$	$\mu_l(p) = e^{\frac{-(y-302)^2}{2\cdot(61.62)}}$	8	large	medium	f_8=-0.1x-0.0004y+37.24
		9	large	large	f_9=-0.06x+0.017y+17.54

[a](x - time; y - pallets)

is 35, 12 of which are non-linear parameters, i.e., premise parameters (parameters of the Gaussian membership function), while the remaining 27 are linear parameters of consequent part (first order polynomials).

The final combination of rules, inference machine logic, numerical interpretation of the rules (f_r), and membership functions ($\mu_i(x)$), is shown in *Table 1*. *Table 1* captures the basic FIS elements, and represents the expert knowledge "caught" and transformed into numerical and logical relations.

4.2 ES Model 2 – CART

The created CART model is used as a complimentary upgrade of the ANFIS model. ANFIS provides an answer on the number of forklifts to be engaged in a particular operation situation. Conversely, CART provides further help to the end users, offering the advice on which forklifts should be engaged. Generally, CART trees are prone to overfitting, and to avoid this, special attention is required while building the tree. In order to create a correct tree model, building the CART model can be summarized in five steps, described in *Figure 4*.

Following the logic of *Figure 4*, the optimal CART model is created. Step 2 produces a tree of 17 nodes. In step 3, several pruned trees are created which are smaller and simpler than the tree in step 2. Step 4 cross-validates the created trees. As the outcome, in step 5, the tree with 15 terminal nodes is chosen as the optimal CART model.

CART model could be represented as a classifier that categorizes observations into one of the k classes, regarding the fact which class k has the largest number of observations in the observed region m. In a given problem, the number of classes is two, since the model classifies forklifts to classes "Yes" and "No". This can be interpreted as to engage (for the model output "Yes") and *not to engage* (for the model output "No"), for the observed forklift in a given operation situation, as presented in *Equation 1*.

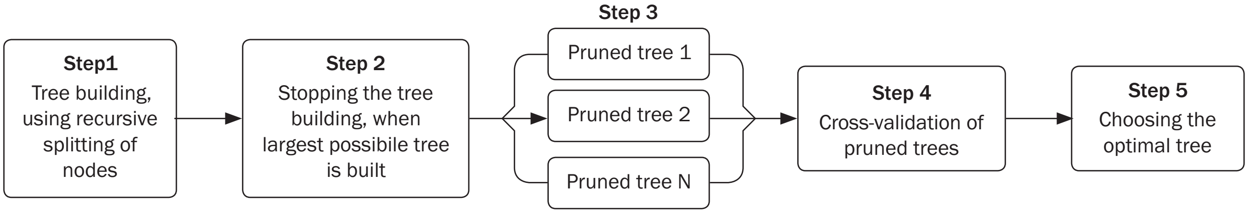

Figure 4 – Methodology steps for building the optimal CART tree model

$$p_{mk} = \frac{1}{N_m}\sum_{xi \in R_m} I(y_i = k); k = 2; \qquad (1)$$

y_i - i-th observation in region m, m=15;

p_{mk} - proportion of class k observations in the node m;

N_m - number of training observations in the region m.

5. EVALUATION OF ES MODELS

5.1 Evaluation of ES Model 1

In order to evaluate and confirm that the ANFIS model is the best ES that can be used in a given problem, several other models are created and tested on the test data, as seen in *Table 2*. For the evaluation of the model, the root mean square error (RMSE), adjusted mean average percentage error (MAPE) and R^2_{test} are used, as seen in *Equation 2*.

Table 2 – Comparative review of different ML models

Models	RMSE	Adjusted MAPE	R^2_{test}
ANFIS[a]	1.57	18%	93%
Extended linear model[b]	2.02	38%	84%
GAM[c]	2.51	53%	74%
Extended GAM[d]	1.71	24%	89%
CART[e]	2.54	38%	81%
Random forests[f]	1.88	18%	85%
Boosting[g]	1.60	25%	92%

[a] *Details about ANFIS model are provided in section 4.1.*

[b] *$y=74.8-33.46 \cdot \log x_1+3.6 \cdot (\log x_1)^2+0.059 \cdot x_2-2.11 \cdot 10^{-4}\, x_1\, x_2$;*
(x_1- time, x_2 - pallets).

[c] *$y=4.17+f_1(x_1)+f_2(x_2)$; f_i - smooth splines with the degrees of freedom of 8 and 1.*

[d] *$y=4.17+f_1(x_1)+f_2(x_2)+f_3(x_1\, x_2)$; f_i - smooth splines with the degrees of freedom of 9, 1 and 17;*

[e] *$f(x)=\sum_{m=1}^{M} c_m I(x \in R_m)$; M - number of terminal nodes (M=8);*
$c_m = \frac{1}{N_m}\sum_{i \in N_m} y_i$; c_m= (3.6, 9.6, 25.2, 12.4, 2.1, 6.9, 12.6, 3.4).

[f] *$\hat{f}_{randFor}(x) = \frac{1}{B} = \sum_{b=1}^{B} \hat{f}^{*b}(x)$; B - total number of fitted trees (B=400); tree depth=2.*

[g] *$\hat{f}(x) = \sum_{b=1}^{B} \lambda \hat{f}^{b}(x)$; λ=0.05; d - number of terminal nodes (d=3); B=1,300.*

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(A_i - F_i)^2};$$
$$Adj.MAPE = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{|A_i - F_i|}{|A_i| + |F_i|}\right);$$
$$R^2_{test} = \left(\frac{\sum_{i=1}^{N}(A_i - \overline{A})\cdot(F_i - \overline{F})}{\sqrt{\sum_{i=1}^{N}(A_i - \overline{A})^2 \cdot \sum_{1}^{N}(F_i - \overline{F})^2}}\right)^2; \qquad (2)$$

where $\overline{A} = \frac{1}{N}\sum_{i=1}^{N} A_i$; $\overline{F} = \frac{1}{N}\sum_{i=1}^{N} F_i$; A_i- actual (desired) values, F_i- fitted (predicted) values, N – number of test observations.

From *Table 2* it can be concluded that Boosting and ANFIS achieve similar RMSE and R^2_{test}; nevertheless, ANFIS has lower MAPE. Therefore, it can be concluded that the ANFIS model has better properties than competing models, and that the ANFIS model makes similar decisions as the expert in the same organization situations.

5.2 Evaluation of ES Model 2

For the evaluation of the mismatch between the expert decisions and the model predictions, regarding the issue of which forklifts should be engaged, the misclassification rate and F1 score are used (see *Equation 3*):

$$Misclassification\, rate = \left(1 - \frac{(t_p + t_n)}{N}\right)\cdot 100\%;$$
$$F_1\, score = 2 \cdot \frac{\left(\frac{t_p}{t_p + f_p}\right)\cdot\left(\frac{t_p}{t_p + f_n}\right)}{\left(\frac{t_p}{t_p + f_p}\right) + \left(\frac{t_p}{t_p + f_n}\right)} \cdot 100\% \qquad (3)$$

where t_p – true positive, t_n – true negative, f_p – false positive, f_n – false negative.

The comparison of different models is provided in *Table 3*. From *Table 3* it can be concluded that the CART and Logistic regression show best performances. It is interesting to notice that tree-based models again show excellent prediction performances and in this case, outperform ANFIS, LDA and KNN. Bearing in mind the prediction accuracy from *Table 3*, it can be concluded that the CART model demonstrates best overall performances, given the observed problem of forklift engagement.

Table 3 – Comparative review of different ML models

Models	Misclassification test rate	F1 score
ANFIS[a]	18%	84%
Logistic regression[b]	8%	90%
LDA[c]	10%	88%
KNN[d]	26%	69%
CART[e]	7%	92%
Random forests[f]	11%	87%
Boosting[g]	12%	86%

[a] *Neural network has 16 inference rules and 104 parameters (24 nonlinear and 80 linear).*

[b] $p(x) = \frac{e^{-1.01-44.63x_1-7.37x_1^2+0.07x_2-0.06x_4}}{1+e^{-1.01-44.63x_1-7.37x_1^2+0.07x_2-0.06x_4}}$;
x_1- activity importance; x_2 - AFU; x_3- distance; x_4- FU.

[c] $\delta_k(x) = x^T \Sigma^{-1}\mu_k - \frac{1}{2}\mu_k^T \Sigma^{-1}\mu_k + \log(\pi_k)$;

$$\delta_0 = x^T \begin{bmatrix} 0.93 \\ 0.09 \\ 0.06 \end{bmatrix} - 8.4; \delta_1 = x^T \begin{bmatrix} 0.46 \\ 0.11 \\ 0.04 \end{bmatrix} - 6.3; x = \begin{bmatrix} x_1 \\ x_2 \\ x_4 \end{bmatrix}$$

[d] $Pr(Y = j \mid x = x_0) = \frac{1}{K}\sum_{i \in N_0} I(y_i = j)$; *j=2; K - number of closest training examples in the feature space (K=42).*

[e] *Details about the CART model are provided in Section 4.2.*

[f] $\hat{f}_{randFor}(x) = \frac{1}{B}\sum_{b=1}^{B} \hat{f}^b(x)$; *B=400; m - number of variables used in fitting each tree (m=4).*

[g] $\hat{f}(x) = \sum_{b=1}^{B} \lambda \hat{f}^b(x)$; *λ=0.05; d - number of splits in each tree (d=4); B=2,700.*

6. DISCUSSION AND KNOWLEDGE TRANSFER

Based on the previously created FIS elements (*Table 1*), as the final output of the ES model 1, FIS graphical interface emerges (*Figure 5*). The interface allows operators to make decisions simply and easy regarding the number of forklifts to be employed just by moving the vertical line through the domain of input variables, depending on the time and cargo defined for the loading.

ES model 2 is a supplementary tool to the ES model 1, and it provides further help in decision making by offering information whether the particular forklift should be engaged in the loading zone (*Figure 6*). Having the information on the position of a forklift (distance from the loading zone), its current activity (importance of activity), utilization of working hours (FU), and average utilization of all forklifts (AFU), the user can easily decide whether the observed forklift presents a good choice for being deployed in the loading zone, or if some other forklift should be picked. The CART decision tree is very easy to interpret and there is no need for entering the input values into software; instead, the tree from *Figure 6* can be printed and placed on a visible location in the warehouse.

Managers can use the presented ES models daily, which helps users achieve higher supply chain responsiveness to customer demands by enabling a high level of probability of the on-time delivery. Also, ES models provide training for novice managers who become more and more experienced by using them.

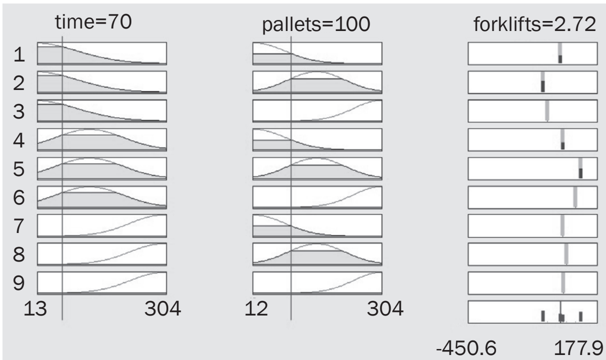

Figure 5 – FIS interface (premise, output)

The proposed approach demonstrated successful results in acquiring the expert's "know-how" knowl-

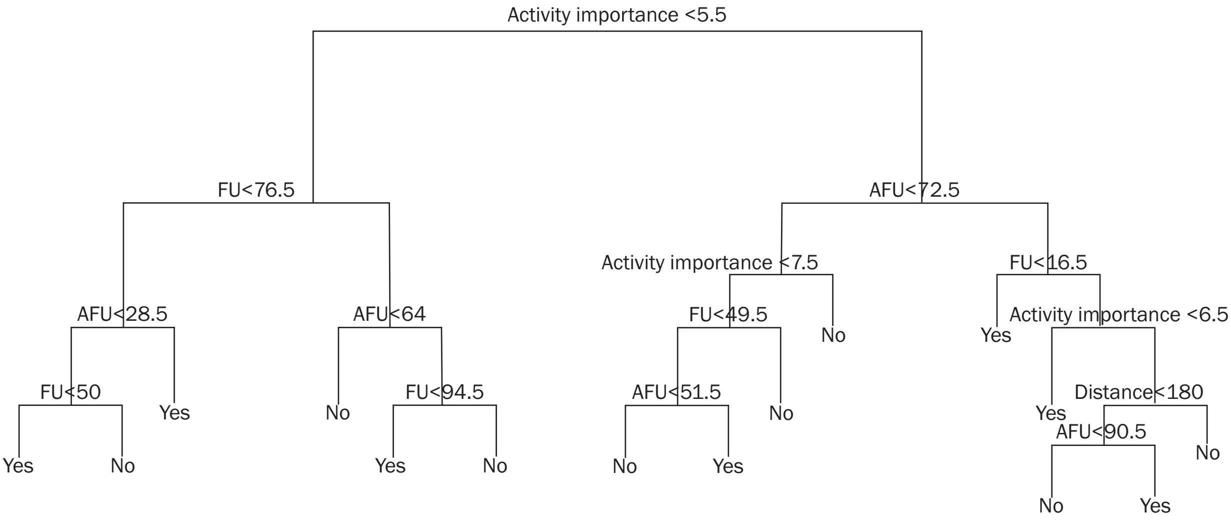

Figure 6 – CART decision tree regarding forklift engagement

edge and in capturing their "inference logic". Following the described approach, the path for extracting and further using the manager's "know-how", from other warehouse operations, is demonstrated. This is very important for practitioners, since engaging experts in the warehouse field is usually expensive. Therefore, ESs that can simulate manager's decisions are tools that can bring significant savings and rationalization in the warehouse business.

Research limitations are related to the knowledge basis of the created ESs, which are extracted from only one manager. In order to extrapolate ES models to other beverage warehouses, the participation of more managers in knowledge acquisition is needed. Furthermore, since literature lacks scientific papers dealing with the models for engaging forklifts in the warehouse operations, future research should be focused on creating the ES models that support decision makers while deciding on the engagement of forklifts in other warehouse and factory activities, or warehouses in other industries, and integrating them in the enterprise resource planning system of the company. For that purpose, we encourage using the adopted methodology (*Figure 1*) and logic from [7, 8], as well as the presented ML techniques.

7. CONCLUSION

In order to overcome the problem of the proper engagement of forklifts and to have a better foundation for future engagement decisions, two ES models are presented as part of DSS for the engagement of forklifts in the loading zone. In the described system, based on a real case, ANFIS and CART show best results; thus, they are chosen for practical application (Tables 2 and 3). Statistical tests have shown that there is a significant correlation between the desired (expert decisions) and model predictions. Therefore, the proposed models can be used as a decision-making support tool, as a training tool for young managers, or to completely replace the expert at moments when the expert is absent or unavailable. The presented case study, used for ESs development, is related with the beverage industry. It would be very interesting to further explore applicability of presented methodology and ML techniques in other industries.

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RAZVOJ EKSPERTSKIH SISTEMA ZA PROGNOZIRANJE POTREBNOG BROJA VILJUŠKARA NA OPERACIJI UTOVARA

REZIME

U prezentovanom radu fokusirali smo se na problem angažovanja viljuškara na procesu utovara tereta u centralnom skladištu. Koristeći metodologiju ekspertskih sistema, kreirana su dva modela. Modeli su bazirani na tehnikama mašinskog učenja. U radu je korišćeno nekoliko tehnika mašinskog učenja, kako bi se odabrale najbolje za posmatrani slučaj. Cilj modela jeste „kopiranje“ ekspertskog znanja i njegova transformacija u numeričko-logičke veze. U tu svrhu, kreirani su i međusobno upoređeni različiti modeli mašinskog učenja. Najbolje rezultate pokazali su ANFIS neuronska mreža i CART regresivni-klasifikacioni algoritam. Navedeni modeli primenjeni su u centralnom skladištu industrije pića. Kreirani ekspertski sistemi predstavljaju novi pristup za racionalizaciju korišćenja viljuškara, naročito za rešavanje problema angažovanja viljuškara na procesu utovara. Modeli su jednostavni, laki za razumevanje, pouzdani i praktično primenjiv alat za donošenje svakodnevnih operativnih odluka vezanih za angažovanje viljuškara na operacijama utovara tereta.

KLJUČNE REČI

viljuškari; utovar tereta; ekspertski sistemi; mašinsko učenje; ANFIS; CART;

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