

A NEW APPROACH FOR RULE ESTIMATION OF FUZZY INFERENCE SYSTEM: A CASE STUDY FOR PUBLIC TRANSPORT MAINTENANCE SYSTEM



¹Düzce Üniversitesi, Mühendislik Fakültesi, Endüstri Mühendisliği Bölümü, Düzce, TÜRKİYE ²Yıldız Teknik Üniversitesi, Makine Fakültesi, Endüstri Mühendisliği Bölümü, İstanbul, TÜRKİYE ¹melikeerdogan@duzce.edu.tr, ²ihkaya@yildiz.edu.tr

(Geliş/Received: 02.01.2020, Kabul/Accepted in Revised Form: 24.08.2020)

ABSTRACT: The increase in the population and the high amount of individual vehicle usage in the big cities brought traffic congestion and environmental problems. Additionally, these issues have also some negative effects on the public transport systems (PTSs). In this respect, the analysis of PTS is critical and important for both city life and people. It is possible that the failures in PTS can lead to many problems. Disruption of daily life, loss of lives and property or damage to the environment are only just a few of these problems. In this context, effective maintenance planning for PTSs is so crucial. In this study, the rule estimation for a fuzzy rule-based system (FRBS) which takes into consideration many factors for the maintenance planning of PTSs is discussed. The rule-based system for maintenance planning of Bus Rapid Transit System (BRT) will be highly effective for the prediction of failures for PTSs and the correct actions to be taken. Rule estimation for this system is aimed to increase the precision and flexibility of maintenance procedures. In this context, a model based on artificial neural networks (ANNs) has been developed and used in rule estimation for FRBS. For this aim, ten cases that are not in the rule base system are estimated and the results of the fuzzy rule-based maintenance inference system for the relevant inputs are revealed. Thus, it has been shown that ANNs can be used effectively for the analysis of rules that are not included in the current rule-based maintenance system.

Key Words: Artificial Neural Networks, Bus Rapid Transit, Estimation, Fuzzy Based Rule System.

Bulanık Çıkarım Sisteminde Kural Tahmini için Yeni Yaklaşım: Toplu Taşıma Bakım Sistemi İçin Bir Örnek Olay Çalışması

ÖZ: Büyük şehirlerde yaşanan nüfus artışı ve bireysel araç kullanımının artması, trafik problemini de beraberinde getirmiştir. Bu durumların neticesinde toplu taşıma sistemlerinin de olumsuz etkilendiği söylenebilir. Bu anlamda toplu taşıma sistemlerini (TTS) analiz etmek, hem şehir hayatı hem de toplu taşıma kullanıcıları için oldukça kritik ve önemlidir. Toplu taşıma sistemlerinde meydana gelebilecek herhangi bir arızanın birçok sorunu beraberinde getireceği söylenebilir. Günlük hayatın aksaması, can ve mal kayıpları ya da çevreye verilen zarar bu sorunlardan yalnızca birkaçıdır. Bu kapsamda, toplu taşıma sistemlerinin bakım planlama yapılması çok önemlidir. Bu çalışmada, toplu taşıma sistemlerinin bakım planlama yapılması çok önemlidir. Bu çalışmada, toplu taşıma sistemlerinin tahmini ele alınmıştır. Metrobüs sisteminin bakım planlamasından kullanılacak kural tabanlı bu sistem, toplu taşıma sistemlerinde olan arızalar ve bu arızalar karşısında alınacak aksiyonların öngörülmesinde oldukça etkili olacaktır. Bu sistem için önerilen kural tahmini ile bakım prosedürlerinin kesinliğinin ve esnekliğinin arttırılması amaçlanmaktadır. Bu kapsamda, çalışma kapsamında yapay sinir ağları (YSA) geliştirilmiş ve kural tahmini için kullanılmıştır. Bu amaçla, kural tabanında yer almayan on adet durum için tahminleme yapılarak ilgili girdiler için bulanık kural tabanlı bakım çıkarım sisteminin hangi

sonuçları ortaya koyduğu belirlenmiştir. Böylece, YSA'nın mevcut kural tabanlı bakım sistemine dahil olmayan kuralların analizi için etkili bir şekilde kullanılabileceği gösterilmiştir.

Anahtar Kelimeler: Yapay Sinir Ağları, Metrobus, Tahmin, Bulanık Kural Tabanlı Sistem.

1. INTRODUCTION

With the rapid increase of the population in the big cities and consequently the traffic intensification, public transport has become more and more used. Therefore, this causes the vehicles to wear out more quickly. Failures that may occur in public transport vehicles directly affect human life and city traffic. The maintenance applications for public transport vehicles are critical both for the passengers and the general operation of transportation, especially in crowded cities. In this sense, if timely and correct interventions are performed, failures can be prevented and accidents can also be avoided. There are few studies in the literature addressing failures in public transport and maintenance planning. However, none of them is related to the instantaneous monitoring of failures and making the maintenance decision required for the vehicles. The first study in this context is to create a maintenance decision support system (DSS) for metrobus which is the bus rapid transit system (BRT) (Erdoğan 2018). This system will provide an infrastructure for the maintenance or renewal decision, taking into account the cost, impact and other characteristics of the failures.

The proposed DSS by (Erdoğan 2018) provides recommendations on the measures to be taken in case of failure on metrobus which is the BRT system using in İstanbul, Turkey. With this DSS, the vehicles in the BRT system can be monitored instantly and in the case of failure, decisions for maintenance can be made immediately by taking into consideration many inputs determined before. These decisions can be made without the need for a human decision-maker utilizing the proposed DSS. To model the uncertainties in the process, to incorporate the linguistic evaluations of the decision-makers and to achieve closer results to reality, decision-making under uncertainty approaches are applied. First of all, the failures have been prioritized by using fuzzy and stochastic MCDM methods. Then, taking into account the priorities of failure which is an input for FRBS, the other input variables such as reliability, cost, etc. have been determined and their membership functions have been extracted. Finally, a rule-based DSS has been created for supporting the maintenance planning for BRT. By comparing the current situation with the proposed situation, the advantages of the proposed method are determined and the validity and sensitivity analyzes of the model are also examined. After all these stages, a maintenance DSS has been established in which the maintenance decision can be taken instantly, the failures can be followed and the vehicle conditions can be kept under control.

After this point, in this paper, an ANNs-based estimation approach is proposed to update the rulebased system and to add new rules into the system. The rules that are unpredictable, unexpected, or undefined on the proposed FRBS are estimated by applying ANNs in the data mining software WEKA.

The estimation process can be successfully performed with ANNs approach which can provide nonlinear modeling without any prior knowledge between input and output variables or without making any assumptions (Hamzaçebi and Kutay 2004). Estimation can also be applied efficiently when the input and/or output variables are qualitative or quantitative. At this point, it is also reasonable to apply the estimation of unspecified rule results in rule-based systems whose inputs and outputs are qualitative variables. In this study, the estimation study has been conducted by using this feature of ANNs for the proposed DSS by (Erdoğan 2018).

The rest of this paper has been organized as follows: Section 2 includes brief information about the studies on the maintenance of public transportation by using ANNs. Section 3 provides the estimation methodology for the FRBS of BRT maintenance planning. Section 4 presents a real case study for BRT maintenance applying FRBS. Finally, Section 5 gives conclusions and future suggestions.

2. ARTIFICIAL NEURAL NETWORK STUDIES IN TRANSPORTATION AND MAINTENANCE AREAS

Artificial neural networks (ANNs) are an approach that can be applied in many different areas for estimation. It is generally used in the field of transportation and maintenance for the same purpose. However, there is no paper about the maintenance planning of public transportation vehicles which adopted ANNs method. ANNs have been used to solve problems such as transportation mode selection (Hussain et al. 2017), real-time dynamic transit signal priority optimization (Ghanim and Abu-Lebdeh 2015), determination of bus stop and passenger activity times (Motamed et al. 2012), dynamic public transport passenger flow prediction (Ma et al. 2011). It has been used in many different studies in the field of maintenance such as the evaluation of the renewal process of a mechanism in the maintenance system (Duer 2011), condition-based estimated maintenance (Krenek et al. 2016), anomaly in energy consumption for condition-based maintenance in compressed air generation systems (Santolamazza, Cesarotti, and Introna 2018), estimating tractor repair and maintenance costs (Rohani, Abbaspour-Fard, and Abdolahpour 2011). In this study, it is aimed to determine the behavior of the rule-based system by estimating it with ANNs approach when situations that have not been encountered before in the case of failures. With this study, ANNs have been used for the first time in the maintenance applications of public transport vehicles. In this respect, we believe that our paper will be a prominent study for the combination of application method and area.

3. ESTIMATION OF RULES NOT INCLUDED IN THE RULE-BASED SYSTEM

An FRBS has been created for determining the maintenance policy of the BRT system used in Istanbul in the study of Erdogan (2018) (Erdoğan 2018). In that paper, eight inputs named as Failure Frequency (AYS), the period in which the vehicle is in use (AKD), Vehicle Age (AY), Importance level of failure (ADT), Failure Cost (AML), Vehicle Reliability (GUV), Time After Previous Maintenance (BUGS), Driver Ability (SY) and four outputs Continue to Use (KDE), Take the Vehicle to Service at a Convenient Time (UZB), Take the Vehicle to Service in Urgently (ABA), Remove vehicle from use(AKK) had been identified to be used in the FRBS. Table 1 shows the levels of the inputs with the abbreviations used and Table 2 shows the details for outputs.

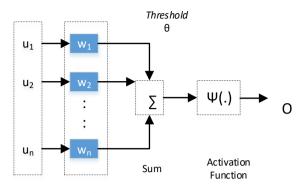
Table 1. Levels of inputs					
Input	Levels				
Failure Frequency (AYS)	Low, Middle, High, Higher, Highest				
The period in which the vehicle is in use (AKD)	Summer, Winter				
Vehicle Age (AY)	Young, Middle, Old				
Importance level of failure (ADT)	Unimportant, Medium Important, High Important				
Failure Cost (AML)	Low, Middle, High				
Vehicle Reliability (GUV)	Low, Middle, High, Higher, Highest				
Time After Previous Maintenance (BUGS)	Short, Middle, Long				
Driver Ability (SY)	Low, Good, Middle, Experienced,				
	Professional				

	Table 2. Levels of outputs
Output	Explanation
KDE	Continue to Use
UZB	Take the Vehicle to Service at a Convenient Time
ABA	Take the Vehicle to Service Urgently
AKK	Remove vehicle from use

Constructing an FRBS for maintenance planning of the metrobus was begun by identifying membership functions for relevant inputs and outputs (Erdoğan 2018). Then, 75 rules were determined with the information obtained from the experts and the proposed DSS was established, in which the vehicle failures in the metrobuses were observed instantly, to organize the maintenance activities better (Erdoğan 2018). At this point, we handled the problem that users of the proposed fuzzy rule-based DSS may want to update rules over time or run and test the system with different rules. Estimating the new rules is an approach that can be applied at this stage. There are 75 rules in the current FRBS; but given the different levels of the eight inputs, a total of 20250 situations can occur. By estimating the maintenance decisions that will arise with different combinations of inputs, the consequences of these different situations that are not in the rule base can be revealed and added to the FRBS. For this aim, we use the ANNs method to estimate the cases that are not in the proposed FRBS by (Erdoğan 2018). The estimation is performed by applying ANNs in the data mining software WEKA.

3.1. Artificial Neural Networks

Artificial neural networks (ANNs) are an information processing system that is inspired by the structure and function of biological neural networks and learns from examples (Kumar, Nigam, and Kumar 2014). ANNs are known as "universal approximators" and "computational models" with specific features such as learning and adapting, organizing or generalizing data (Kiranyaz et al. 2009). What makes the neural network more flexible and powerful is its ability to learn from examples (Kumar, Nigam, and Kumar 2014). The problem-solving parts of these systems are the process elements called neurons. An ANN associated with these elements is designed and a learning algorithm is implemented to train the network. ANNs usually appear as a model with different number of computational elements that work like biological neurons represented by the "n" layer and where these computational elements between the layers form intense connections (Guneri and Gumus 2008). Multilayer Perceptron (MLP) is the most prevalent neural network model consisting of sequential linear transformations followed by processing with nonlinear activation functions (Avci and Yildirim 2006). The network consists of a series of sensory units (source nodes) that make up the input layer, one or more hidden layers of compute nodes, and an output layer (Gumus, A. T.; Guneri 2009). Each layer calculates the activation function of a weighted sum of the inputs of the layer (Gumus, A. T.; Guneri 2009). With the discovery and widespread use of multilayered neural network training in the 1980s, it was made possible to apply to neural networks as a tool to solve many different problems. Several successful applications of ANNs appear in various fields of mathematics, engineering, medicine, economics, philosophy, economics, finance, meteorology, psychology and neurology (Kialashaki and Reisel 2014). Figure 1 shows the neuron model as an example.



Inputs Weights **Figure 1.** An example of a neuron structure

$$S = w_{1}u_{1} + w_{2}u_{2} + \dots + w_{n}u_{n} - \theta = \sum_{i=1}^{n} w_{i}u_{i} - \theta$$
(1)

$$o = \psi(S)$$
(2)

4. APPLICATION

The FRBS created in the decision-making process regarding the maintenance planning of the metrobus vehicles has 75 rules for 75 different situations. These are the cases where the vehicles have experienced before. However, combinations of inputs other than those previously experienced may also occur in the daily activities of vehicles. These unexperienced combinations may also be desired to be added to the rule-based system. In this study, estimation is made for conditions that may occur out of the determined rules using ANNs approach. WEKA software is used in the estimation process.

WEKA is a java language program developed by Waikato University in New Zealand for use in data mining. In this program, data mining operations such as classification, clustering and association analysis can be performed and pre-processing of data can be performed (Şeker 2015). WEKA is a software that includes machine learning algorithms and data preprocessing tools. This allows quickly to try existing methods in new data sets. With this program, input data is prepared, learning schemes are evaluated statistically, input data and learning outcomes can be visualized. It includes a variety of pre-processing tools as well as many learning algorithms (Witten, Frank, and Hall 2011).

After transferring the rules to WEKA, the ANNs approach is applied to the data by selecting the MultiLayerPerceptron function from the classification tab. WEKA automatically creates a network structure after this selection. Figure 2 shows the network structure visualized by the program.

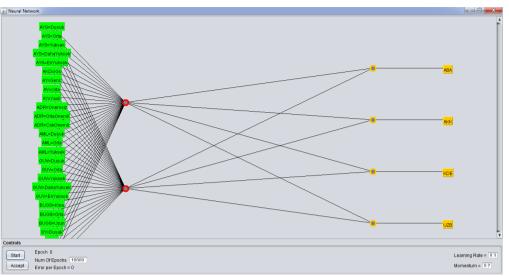


Figure 2. ANNs design created with WEKA program

In order to optimize the ANNs parameters such as learning coefficient, momentum, epoch and number of hidden layers, the grid search algorithm was used. It has been decided to use values for parameters at the highest accuracy degree by increasing or decreasing the related parameters by 0.1 and finally the best values are obtained The parameters used for the ANNs model are determined as 0.3 for the learning coefficient, 0.2 for the momentum, 0.2 for the epoch and 2 for the hidden layers. The results of the model are obtained as shown in Figure 3.

Preprocess Classify Cluster Associ	ate Select attributes	Visualize								
lassifier		I								
Choose MultilayerPerceptron -L 0.3	-M 0.2 -N 10000 -V 0 -S 0	-E 20 -H 2								
est options	Classifier output									
O Use training set										
O Supplied test set Set	Correctly Clas	sified Inst	ances	49		65,3333	ş.			- 1
O Supplied test set	Kappa statisti			0.49	27					
 Cross-validation Folds 10 	Mean absolute			0.19						
O Percentage split % 66	Root mean squa			0.37						
	Relative absol		or	55.25						
More options		Root relative squared error Total Number of Instances			91.5097 % 75					
Nom) SONUC	=== Detailed A	Accuracy By	Class ===							
		TD Date	FD Date	Precision	Recall	F-Measure	MCC	POC Area	PRC Area	Cla
Start Stop		0,500	0,203	0,400	0,500	0,444	0,275	0,656	0,371	ABA
esult list (right-click for options)		0,000	0,029	0,000	0,000	0,000	-0,044	0,869	0,233	AKK
, , ,		0,913	0,058	0,875	0,913	0,894	0,846	0,963	0,882	KDE
14:05:58 - functions.MultilayerPerceptron	Weighted Avg.	0,645 0,653	0,205 0,148	0,690 0,639	0,645 0,653	0,667 0,644	0,446 0,499	0,710 0,787	0,725 0,665	UZB
14:06:52 - functions.MultilayerPerceptron	weighted Avg.	0,035	0,140	0,035	0,000	0,044	0,499	0,707	0,005	
14:07:27 - functions.MultilayerPerceptron	=== Confusion	Matrix ===								
14:14:46 - functions.MultilayerPerceptron										
14:15:23 - functions.MultilayerPerceptron	a b c d	< classi a = ABA	fied as							
14:16:10 - functions.MultilayerPerceptron	8 1 0 7	a = ADA b = AKK								1
		c = KDE								
	7 1 3 20	d = UZB								
										7 -

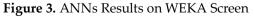


Figure 3 shows the ANNs results with a success rate of 65.3%. Totally, 49 of the 75 data are classified as correct. The model is able to identify samples belonging to all classes. The maximum number of correct

classification is made for 'KDE' output. The output with the lowest rate of correct classification is determined for "AKK", that is, the decision to remove the vehicle from use.

At this point, it can be deduced that some attributes may not have an impact on the classification process and the process of eliminating some of the attributes can be performed to increase the degree of accuracy. Thus, these attributes can be extracted from the data before the classification. One way to measure whether such an attribute is included in the data has an impact on the classification is to create a decision tree. For this aim, a decision tree is created by WEKA to examine whether there is any attribute that has no impact on the classification.

The algorithms used to create a decision tree in the literature are ID3, C4.5, C5.0 and CART. Besides, the J48 algorithm that is developed by the WEKA project team and used to create decision trees, is an open-source Java implementation of the C4.5 algorithm (Bhargava et al. 2018; Yadav and Chandel 2015). The J48 algorithm is applied with the WEKA software to select the input parameters of the ANNs model. The J48 algorithm helps create easy-to-understand models and uses categorical and continuous values (Aljawarneh, Yassein, and Aljundi 2019). J48 creates decision trees from the training dataset, taking advantage of the fact that every feature of the data can be used to make a decision by dividing it into smaller subsets (Bhargava et al. 2018). The algorithm offers a method, known as imputation, identifies missing values according to the existing values and allows the problem of missing values to be solved (Aljawarneh, Yassein, and Aljundi 2019). It also provides greedy method and a tree pruning that helps build small trees and prevent data from over-fitting (Aljawarneh, Yassein, and Aljundi 2019). For all reasons, the J48 algorithm which is also frequently used in the literature is used to create the decision tree. Figure 4 shows the decision tree that is obtained.

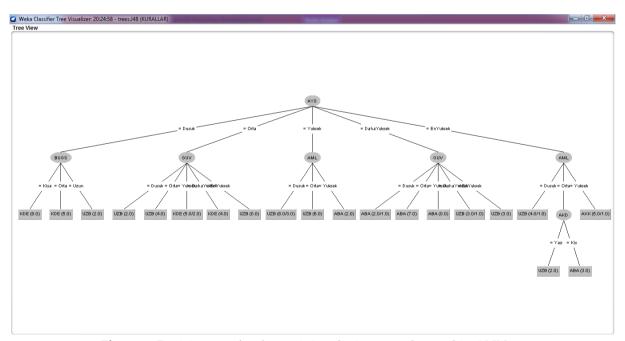


Figure 4. Decision tree for determining the inputs to be used in ANNs

With the decision tree obtained through the program, not all attributes are found to be effective in the classification. The attributes such as vehicle age, importance level of failure and driver ability are inputs that are not included in the classification tree created by WEKA. By subtracting these inputs, a reclassification is performed and the results in Figure 5 below are obtained.

Preprocess Classify Cluster Asso	ciate Select attributes V	isualize									
assifier											
Choose MultilayerPerceptron -L 0.3	I -M 0.2 -N 10000 -V 0 -S 0 -I	E 20 -H 2									
st options	Classifier output										
 Use training set 	=== Summary =										
O Supplied test set Set											- 1
Cross-validation Folds 10	Correctly Cla Kappa statist		ances	54 72 0.5864			\$				- 1
-	Mean absolute			0.55							- 1
Percentage split % 66	Root mean squ			0.35							
More options		Relative absolute error			46.3026 % 84.4772 %						
•	Root relative Total Number			84.47	72 %						
Iom) SONUC	=== Detailed	Accuracy By	Class ===								
Start Stop		TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class	- 1
sult list (right-click for options)		0,688	0,153	0,550	0,688	0,611	0,496	0,748	0,420	ABA	
Succise (right-click for options)		0,000	0,000	?	0,000	?	?	0,857	0,229	AKK	
14:07:27 - functions.MultilayerPerceptron	A	0,913 0,710	0,096 0,159	0,808	0,913 0,710	0,857	0,791 0,557	0,933 0,839	0,846 0,811	KDE UZB	
14:14:46 - functions.MultilayerPerceptron	weighted Avg.		0,135	?	0,720	?	?	0,850	0,699	020	
14:15:23 - functions.MultilayerPerceptron											
14:16:10 - functions.MultilayerPerceptron	=== Confusion	Matrix ===									
14:19:20 - trees.J48	abcd	a b c d < classified as									
14:23:39 - functions.MultilayerPerceptron 14:24:53 - functions.MultilayerPerceptron	11 0 0 5										
14:26:14 - functions.MultilayerPerceptron	5000	b = AKK									
14:28:21 - functions.MultilayerPerceptron	0 0 21 2	c = KDE									
14:30:06 - functions.MultilayerPerceptron		1 u = 025									
14:30:41 - functions.MultilayerPerceptron											t
atus											

Figure 5. Revised ANNs results

As a result of the classification repeated with the reduced attributes, a success with 72% has been achieved. That means the use of this revised data set for predicting new rules will yield more accurate results. Thus, the estimation process is handled with these revised data. After this step, the estimation of the situations that are not found among the rules is performed. For this purpose, 10 new situations which are not included in the rules are defined as randomly. These new situations which are the combinations of the determined inputs with different levels are shown in Table 3:

Table 3. New Rules Table						
Rule/ Result	AYS	AKD	AML	GÜV	BUGS	Output
1	Highest	Winter	Low	Low	Long	?
2	Highest	Summer	High	Low	Short	?
3	Higher	Winter	High	Highest	Long	?
4	Higher	Summer	Low	Higher	Short	?
5	High	Winter	High	Higher	Short	?
6	High	Summer	High	Low	Long	?
7	Middle	Winter	Middle	Middle	Middle	?
8	Middle	Summer	Low	Low	Long	?
9	Low	Winter	High	Low	Long	?
10	Low	Summer	High	High	Short	?

Estimations for these 10 cases that are not in the FRBS by using the ANNs approach in the WEKA program are as shown in Figure 6.

assifier		
Choose ZeroR		
stoptions	Classifier output	
◯ Use training set		
Supplied test set Set		
	Re-evaluation on test set	
Cross-validation Folds 10	User supplied test set	
Percentage split % 66	Relation: KURALLAR	
More options	Instances: unknown (yet). Reading incrementally	
· · · ·	Attributes: 6	
	Predictions on user test set	
lom) Class		
Start Stop	inst# actual predicted error prediction 1 1:2 1:ABA 0.741	
sult list (right-click for options)	2 1:7 1:ABA 0.741	
suit list (right-click for options)	3 1:? 1:ABA 0.741	
14:36:51 - functions.MultilayerPerceptron from file 'revizemodel.mod	107 4 1:7 4:UZB 0.971 5 1:7 4:UZB 0.993	
	6 1:7 4:UZB 0.904	
	7 1:? 4:UZB 0.994	
	8 1:? 4:UZB 0.993 9 1:2 4:UZB 0.803	
	9 1:7 4:UZB 0.803 10 1:2 3:KDE 0.995	
	Summary	
	Total Number of Instances 0	
	Ignored Class Unknown Instances 10	

Figure 6. Estimates for situations not found in the rule-based system

As seen in Figure 6, the program proposed to action of taking the vehicle to service at a convenient time for six cases, estimated that taking the vehicle to service urgently for three cases, and presented that continue of use of the vehicle for one case. Estimation was easily made with the help of ANNs over the FRBS proposed for all kinds of situations that not encountered by metrobus before.

With this study, it is the first time that the estimation process is conducted for the maintenance planning of public transportation vehicles and ANNs, which is the method adopted along with the paper, has proven to be applicable in this area. The use of the estimation approach on maintenance planning of public transport is also encouraged. Due to novelty in this paper, it can be said that this study is a leading paper for researchers and practitioners who want to study in this area.

5. CONCLUSION AND FUTURE SUGGESTION

Planning of maintenance activities efficiently for public transport vehicles is an important issue that needs to be addressed especially for crowded cities in which public transport is used intensively. The most efficient way of planning maintenance activities in public transport vehicles requires multi-faceted analysis and in this sense, the rule-based systems are one of the methods that can be used in the maintenance applications. Therefore, we claim that FRBS proposed in this paper can be used effectively in the maintenance analysis of public transport systems.

In the fuzzy rule-based maintenance system created for BRT vehicles by (Erdoğan 2018), 75 rules have been created for different levels of inputs and a DSS has been established on which maintenance actions should be taken depending on the failures in the vehicles. Except for specified situations, which means determined rules, different situations that occur in FRBS can also be included thereafter. At this point, ANNs can be used to make predictions of the results of new rules as in this study. In this paper, it is aimed to estimate the rules of a fuzzy rule-based maintenance system created within contains 75 rules. For this purpose, ANNs application is carried out in WEKA program and rules which are not in FRBS are estimated. For this aim, ten cases randomly determined and the estimation procedure is performed to reveal the results of them. As a result of the estimation made with all qualitative inputs of FRBS, an approach has been developed to provide more accurate results for the proposed FRBS. Rule estimation for this system is aimed to increase the precision and flexibility of maintenance procedures. It has been shown that ANNs can be used effectively for the analysis of rules and conditions that are not included in the current rule-based maintenance system.

In future studies, the estimation can be performed by using different methods and the validity of the method can be analyzed by comparing with real-life results.

6. REFERENCES

- Aljawarneh, Shadi, Muneer Bani Yassein, and Mohammed Aljundi. 2019. "An Enhanced J48 Classification Algorithm for the Anomaly Intrusion Detection Systems." Cluster Computing 22(5): 10549–65. https://link.springer.com/article/10.1007/s10586-017-1109-8 (June 22, 2020).
- Avci, Mutlu, and Tulay Yildirim. 2006. "Neural Network Based MOS Transistor Geometry Decision for TSMC 0.18µ Process Technology." In Springer, Berlin, Heidelberg, 615–22. http://link.springer.com/10.1007/11758549_84 (June 24, 2019).
- Bhargava, Neeraj, Sakshi Sharma, Renuka Purohit, and Pramod Singh Rathore. 2018. "Prediction of Recurrence Cancer Using J48 Algorithm." In Proceedings of the 2nd International Conference on Communication and Electronics Systems, ICCES 2017, Institute of Electrical and Electronics Engineers Inc., 386–90.
- Erdoğan, M. 2018. "The Recommendation of a Decision Support System for Maintenance Management: An Application for the Public Transportation Process." Yıldız Technical University. https://tez.yok.gov.tr/UlusalTezMerkezi/tezSorguSonucYeni.jsp.
- Gumus, A. T.; Guneri, A. F. 2009. "A Neural Network Based Demand Forecasting System For Two-Echelon Supply Chains." In 13th International Research/Expert Conference "Trends in the Development of Machinery and Associated Technology.
- Guneri, Ali Fuat, and Alev Taskin Gumus. 2008. "The Usage of Artificial Neural Networks For Finite Capacity Planning." International Journal of Industrial Engineering 15(1): 16–25. http://journals.sfu.ca/ijietap/index.php/ijie/article/viewFile/58/30 (December 2, 2018).
- Kialashaki, Arash, and John R. Reisel. 2014. "Development and Validation of Artificial Neural Network Models of the Energy Demand in the Industrial Sector of the United States." Energy 76: 749–60. https://www.sciencedirect.com/science/article/abs/pii/S0360544214010263 (December 2, 2018).
- Kiranyaz, Serkan, Turker Ince, Alper Yildirim, and Moncef Gabbouj. 2009. "Evolutionary Artificial Neural Networks by Multi-Dimensional Particle Swarm Optimization." Neural Networks 22(10): 1448–62. https://www.sciencedirect.com/science/article/pii/S0893608009001038 (December 2, 2018).
- Kumar, Paras, S.P. Nigam, and Narotam Kumar. 2014. "Vehicular Traffic Noise Modeling Using Artificial Neural Network Approach." Transportation Research Part C: Emerging Technologies 40: 111–22. https://www.sciencedirect.com/science/article/pii/S0968090X14000102 (December 2, 2018).

Şeker, Şadi Evren. 2015. Weka Ile Veri Madenciliği. İstanbul: Bilgisayar Kavramları Yayınları.

- Witten, I. H. (Ian H.), Eibe Frank, and Mark A. (Mark Andrew) Hall. 2011. Data Mining : Practical Machine Learning Tools and Techniques. Morgan Kaufmann.
- Yadav, Amit Kumar, and S. S. Chandel. 2015. "Solar Energy Potential Assessment of Western Himalayan Indian State of Himachal Pradesh Using J48 Algorithm of WEKA in ANN Based Prediction Model." Renewable Energy 75: 675–93.