# A DECISION SUPPORT SYSTEM BASED ON NEURO-FUZZY SYSTEM FOR RAILROAD MAINTENANCE PLANNING

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Keywords: Decision Support Systems, Neuro-Fuzzy, Railroad Maintenance

Abstract: Optimization of Life Cycle Cost (LCC) in railroad maintenance, is one of the main goals of the railways managers. In order to achieve the best balance between safety and operating costs, "on condition" maintenance is more and more used; that is, a maintenance intervention is planned only when and where necessary. Nowadays, the conditions of railways are monitored by means of special diagnostic trains: these trains, such as *Archimede*, the diagnostic train of the Italian National Railways, allow to observe every 50 cm dozens of rail track characteristic attributes simultaneously. Therefore, in order to plan an effective on condition maintenance, managers have a large amount of data to be analyzed through an appropriate Decision Support System (DSS). However, even the most up-to-date DSSs have some drawbacks: first of all, they are based on a binary logic with rigid thresholds, restricting their flexibility in use; additionally, they adopt considerable simplifications in the rail track deterioration model. In this paper, we present a DSS able to overcome these drawbacks. It is based on fuzzy logic and it is able to handle thresholds expressed as a range, an approximate number or even a verbal value. Moreover, through artificial neural networks it is possible to obtain more likely the rail track deterioration models. The proposed model can analyze the data available for a given portion of rail-track and then it plans the maintenance, optimizing the available resources.

## 1 INTRODUCTION

This study is addressed to *tamping* operation in railways maintenance. It is compacting and forcing the ballast against the rails and sleepers. Such an operation is frequently carried out by railways companies, with the exception of the new slab tracks, where the ballast is substituted by concrete or asphalt slab.

The aim of the tamping is to improve geometrical parameters of the railway track such as alignment, longitudinal level, super-elevation, gauge and buckling, to reach a higher safety level of the railway.

A variety of mechanical (automated) tamping device are available: they are able to tamp ballast under 2 or 3 sleepers at the same time, thus it is possible to tamp up to 2200 meters of track per hour.

We have to point out that frequently repeated tamping operations could cause negative effect for the ballast. In particular, with respect to the effect on the ballast aging, each tamping cycle is equivalent to a 20 Megatons (MGT) of cumulate traffic, due to increasing of the finer material percentage.

During the life cycle, a given track shows three different phases with respect to the capacity of preserving its original geometrical and morphological characteristics.

For example, let us assume as track quality index a parameter that shows the deterioration of the geometrical layout, such as the standard deviation (SD) of the track alignment. In Figure 1 such a parameter has been connected to the traffic,



Ottomanelli M., Dell'Orco M. and Sassanelli D. (2005).
A DECISION SUPPORT SYSTEM BASED ON NEURO-FUZZY SYSTEM FOR RAILROAD MAINTENANCE PLANNING.
In *Proceedings of the Seventh International Conference on Enterprise Information Systems*, pages 43-49
DOI: 10.5220/0002524500430049

expressed in MGT of trains load, accumulated from the track operation starting. The *aging curve* is made up of three sections: two are curvilinear and one usually is quasi-linear. The aging curve represents the behaviour of the track when no maintenance operations are carried out.

The first portion (a) of the curve is the *youth phase* of the track and it shows a quick increase of the SD, due to an early track settling: the higher SD value is the lower is the ballast compactness. It is very difficult to foresee how long the youth phase lasts since it depends on a number of factors. Moreover, such a phase could be affected also by the part of the railway track we are not dealing with.

The second phase, usually known as *intermediate phase,* is represented by a less than linear curve part (b). This phase starts when the track settling is near to be completed and, consequently, the track aging ratio can be assumed as constant. The intermediate phase lasts for most of the track lifetime; for this reason and for sake of computing simplicity, a lot of algorithms consider only this part of the track lifetime.

The last phase (*old phase*) is representative of the tracks near to the end of the life-time. This curve section (c) shows a quick aging of the track: the value of SD increases in approximately as in exponential way. Generally, in order to preserve railway safety through proper maintenance operations, this phase should be avoided.

Dashed line in figure 1 represents the lower bound of SD, that is the maximum improvement that can be obtained for the track through tamping operations. From the same figure it is possible to note that effectiveness of tamping decreases as the aging of the track increases; thus, starting from a certain time, it should be more economical to renew ballast, rails or sleepers than carrying out tamping operations since they would become more frequent and less effective.

Existing Decision Support Software (DSS), such as *Ecotrack*, usually has the following drawbacks:

**a)** the phases *a* and *c* are not taken into account, thus the aging function is assumed to be linear for the whole life-time of the track;

b) the considered aging function is assumed to be the same for the whole rail track;

**c)** such models assume as intervention thresholds some rigid and crisp values.

Actually, the approximation imbedded in the point 1) is not suitable from the safety standpoint. In fact, because of several different reasons such as bad maintenance programs or problems concerning local conditions of the superstructure or roadbed, the track deterioration could be quicker than linear. In this case, the thresholds should be crossed sooner than the DSS foresaw.

In figure 2 such a situation is depicted referring to a 200m long track segment. Track alignment was observed each 50 cm, then 400 observations are

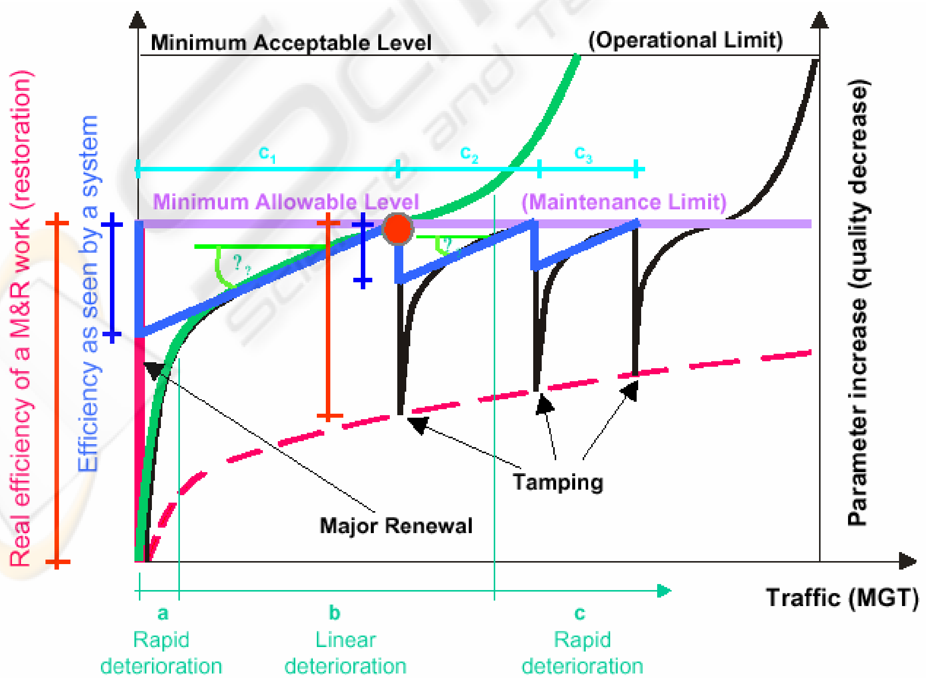


Figure 1: Aging Function

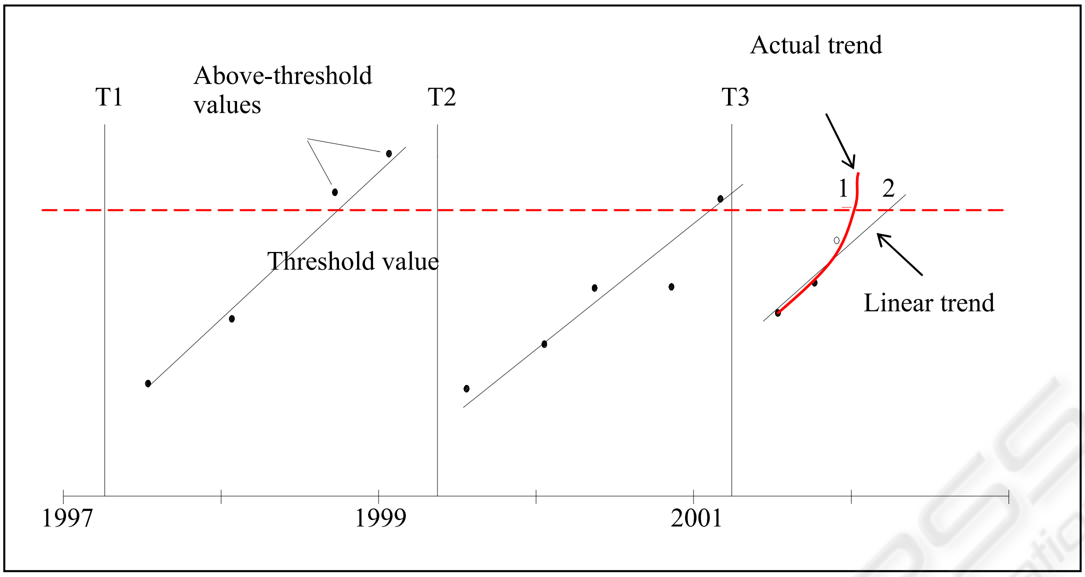


Figure 2: Example of incorrect extrapolation

available for each segments: on the basis of the observed values, the DSS determines the Standard Deviation (SD). The ordinates represent the value of SD for the alignment with respect to time. The vertical lines T1, T2 e T3 represents the tamping that have been carried out in the last years. The horizontal dashed line represents the threshold value suggested by the *European Rail Research Institute* (ERRI) for the acceptability of the observed parameter.

From the figure 2, it is possible to see that linear extrapolation of SD can mislead, since in case the track-segment is in its *old phase* -as frequently happens in reality, the date for tamping maintenance would be later than necessary.

Concerning the statement 2), it has to be pointed out that different track-segments usually have different geometrical deterioration trend and different wear and tear of the rails, even under the same load conditions.

European railways companies have widely verified this issue, thus the general three-phases shape of the aging function (figure 1) should to be adjusted for each track-segment in order to take into account local characteristics of the track.

The issue in the statement 3) has got conceptual origin. Traditional DSS's are quite rigid, since they assume crisp values for the thresholds: as the observed parameter exceed the threshold, the decision rule suggests maintenance. An example of this kind of rule could be:

**IF** (SDalignment > 1.4) **THEN** tamping

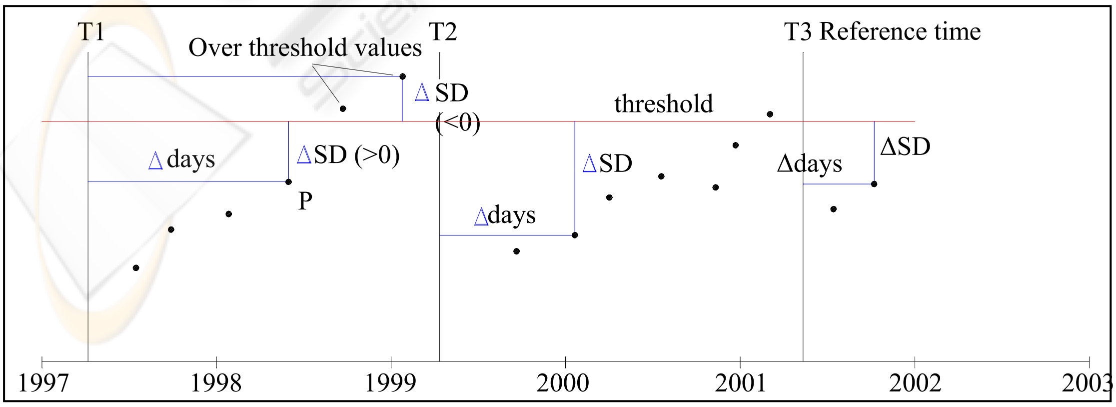


Figure 3: Scheme of the variation of quality indexes.

This approach does not allow to take into account how much the threshold has been exceeded; in fact, such a DSS gives the same importance to very different values of the SD, for example 1.4 and 3.0. In other words, it gives the same importance when the SD of the parameter exceeds "*very slightly*" or "*heavily*" the given threshold.

## 2 METHODOLOGY

In order to overcome some of the mentioned drawbacks of traditional DSS, in this paper we propose a new methodology based on an Adaptive Network-based Fuzzy Inference System (ANFIS). Using the proposed ANFIS algorithm, it is possible to calibrate the Membership Functions (MF) of the Fuzzy Inference System (FIS), with reference to a given track-segment. Subsequently, the results obtained by the proposed model have been compared to those obtained by using Ecotrack.

To test the robustness of the two DSS, we also simulate some rough errors in data observation.

The FIS has been applied to 200 m long track-segment. In figure 3 is the scheme of changes in time of the track-segment quality indexes. The proposed Fuzzy Inference System has been specified with three input elements and one output element; in particular as input elements we have considered the SD of alignment, the SD of vertical level and the number of days past from last tamping. As output the FIS provides with an estimate of the date for tamping works on the track-segment.

The Standard Deviations of the two input parameters have been represented through the following five Gaussian Membership Functions (MF):

low, low-medium, medium, medium-high, high.

The output is made up of singletons, indicating the number of days, starting from the date of the analysis, before the next tamping.

The time period "*Ddays***"** is the number of days between the tamping carried out straight before each measurement and the date of the survey **P**, while $DSD_{\text{alignment}}$ and $DSD_{\text{vertical}}$ are respectively the differences between given threshold values and the SD of alignment and the SD of longitudinal level. It is evident that, if the threshold value is exceeded, the differences DSD reach negative values.

Such a FIS has been calibrated through an ANFIS algorithm: all the MFs have been calibrated by *training* the Artificial Neural Network (ANN) relevant to the FIS. The structure of the adaptive ANN is chosen by the analyst, which chooses also the number of MF to be associated to each input and output. The ANN represents an analytical tool able to learn and emulate the behaviour of a real system. The ANN for a given time interval operates side by side with the real system (training phase) and modifies its characteristics until the error done is minimised. The characteristics of the ANN of the given ANFIS, such as input and output nodes and the number hidden layers are relevant to the FIS. Given a certain number of input–output pairs, the error ε is the difference between the output value Y* determined by the ANN and the "true" output value Y (so-called "pattern"):

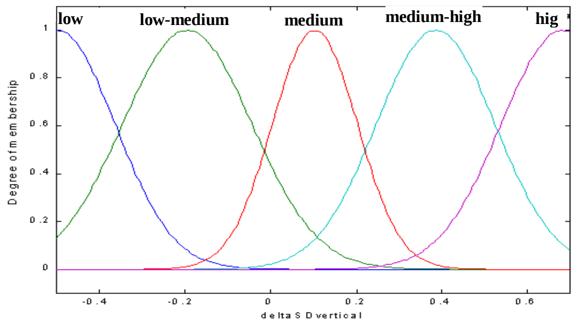


Figure 5: Membership function for ΔSDvertical

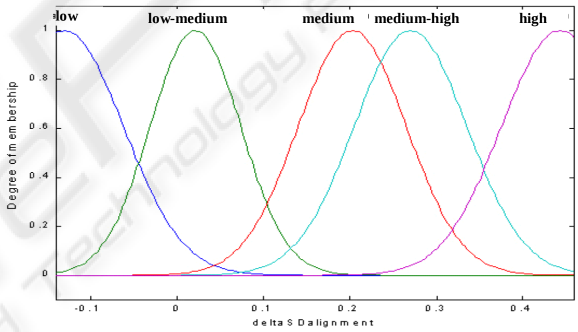


Figure 4: Membership function for ΔSDalign.

$$\varepsilon = |Y^* - Y| \qquad (1)$$

The characteristics of an adaptive ANN are the node functions, which correspond to the MF of the FIS. Those functions are to be calibrated during the training phase. The node functions correspond to the Membership Functions of the FIS referring to; such a functions are calibrated during the training phase.

## 3 MODEL SPECIFICATION AND CALIBRATION

To carry out the specification and calibration of the proposed model, a 200 m long track-segment has been considered. The following features were available for this segment:

– maximum speed of the railway line 140 km/h;
– laying date for all components of the track, like ballast, rails, sleepers and fastenings, 1/1/1985;
– during the period February 1992 - July 2002, ten measurements a year for SD alignment and SD vertical level have been carried out;
– in the same period, three tamping have been carried out, namely in January '92, August '96, October 2001;
– the period from 1/1/2003 to 31/12/2007 has been considered as planning period.

On the basis of the International Railways Union (UIC) rules, the maximum acceptable value for SD alignment is 1.4, while for SD vertical level is 2. In this paper, three input and one output has been chosen for the FIS; the output is the date of intervention, while the input are $\Delta SD_{alignment}$, $\Delta SD_{vertical}$, Δdays, where:

– ΔSDalignment = 1.4 – measured SD alignment;
– ΔSDvertical = 2.1 – measured SD vertical level;
– Δdays are the days past from the last tamping.

A set of 107 pairs of input- output vectors has been used; in the table 1 a sample of the input database is reported.

Table 1: Example of the input database

| DATE | $SD_{align.}$ | $SD_{vert.}$ | $\Delta SD_{align}$ | $\Delta SD_{verti}$ | Δdays |
|---|---|---|---|---|---|
| 15/1/92 | 1,23 | 1,78 | 0,17 | 0,32 | |
| 27/1/92 | TAMPING | | | | |
| 15/2/92 | 0,88 | 1,06 | 0,52 | 1,04 | 18 |
| 15/3/92 | 0,87 | 1,08 | 0,53 | 1,02 | 48 |
| 15/4/92 | 0,89 | 1,08 | 0,51 | 1,02 | 78 |
| 15/5/92 | 0,89 | 1,12 | 0,51 | 0,98 | 108 |
| 15/7/92 | 0,91 | 1,12 | 0,49 | 0,98 | 168 |
| 15/8/92 | 0,89 | 1,16 | 0,51 | 0,94 | 198 |
| 15/9/92 | 0,89 | 1,14 | 0,51 | 0,96 | 228 |
| .... | .... | .... | .... | .... | .... |
| 15/4/01 | 1,26 | 2,38 | 0,14 | -0,28 | 1667 |
| 15/5/01 | 1,53 | 2,53 | -0,13 | -0,43 | 1697 |
| 15/7/01 | 1,52 | 2,5 | -0,12 | -0,4 | 1757 |

Table 2: Results of the tests

| | | | | | |
|---|---|---|---|---|---|
| 15/8/01 | 1,5 | 2,52 | -0,1 | -0,42 | 1787 |
| 15/9/01 | 1,54 | 2,59 | -0,14 | -0,49 | 1817 |
| 11/10/01 | TAMPING | | | | |
| 15/10/01 | 1 | 1,65 | 0,4 | 0,45 | 4 |
| 15/11/01 | 1,03 | 1,65 | 0,37 | 0,45 | 34 |
| 15/1/02 | 1,05 | 1,68 | 0,35 | 0,42 | 94 |
| .. | .. | .. | .. | .. | .. |
| 15/5/02 | 1,09 | 1,78 | 0,31 | 0,32 | 214 |
| 15/7/02 | 1,11 | 1,84 | 0,29 | 0,26 | 274 |

This set of input vectors has been divided into two groups:

– training vectors, used for training a neural network, that will subsequently calibrate the MF's;
– checking vectors, used to check the model.

The MF's used in our case are gaussian curves, characterized by mean and standard deviation; the output is a singleton.
The training results consist in calibrated MFs both for input and output, as well as the rules of the inference engine. In the following figures 4 and 5 the MF's for $\Delta SD_{alignment}$ and $\Delta SD_{vertical}$, respectively, are reported. Of course, when both $\Delta SD_{alignment}$ and $\Delta SD_{vertical}$ are 0, the thresholds are reached; then, the pair [0 0] as input allows to forecast when these thresholds will be reached.
Note that not necessarily both thresholds will be reached at the same moment. On the contrary, highly likely this situation will never happen.
The proposed FIS uses the logical **OR** to get the lowest value ΔSD as a precautionary condition. In figure 6 are the rules of inference system obtained by ANFIS.

## 4 ROBUSTNESS OF THE METHOD TEST

A glaring mistake in measurement has been simulated: one of the measured values has been put over threshold, keeping hold other values. Table 2 shows the results of tests for different location of the error; in particular, in the test 4 an error in the second-last measure of SD of alignment has been simulated. It is easy to see that the influence of a measurement error on the FIS forecast is very low, not greater than 8%. The reason is that the system decision is based not only on a unique peak value, but on an overall analysis of the trend, over time, of the track parameters.

## 5 CONCLUSIONS

Tamping 11 October 2001

| Test | Notes | date of measure | SD align | SD vert. | days to intervention | Δdays % |
|---|---|---|---|---|---|---|
| 1 | reference | 15-july-02 | 1,11 | 1,84 | 713 | 0 |
| 2 | error on last measure | 15-july-02 | 1,06 | 1,74 | 736 | 3.22 |
| 3 | error on fifth-last measure | 15-febr-02 | 1,02 | 2,11 | 760 | 6.59 |
| | | 15-july-02 | 1,11 | 1,84 | | |
| 4 | error on second-last measure | 15-may-02 | 1,09 | 2,11 | 765 | 7.29 |
| | | 15-july-02 | 1,06 | 1,84 | | |
| 5 | error on last measure | 15-july-02 | 1,11 | 2,11 | 718 | 0.70 |

Main advantages in using such a kind of FIS are flexibility, since thresholds are no longer crisp, and versatility, since the forecast is carried out for each specific track-segment and the method allows to take into account the company policy as for maintenance. Moreover, it is possible to use the expert knowledge, without predefined mathematical models: in this sense, the fuzzy inference is close to reasoning way of railway officials and technicians.

The proposed model is also able to recognize glaring mistakes in measurement, since it analyzes the overall behavior of the track on the basis of the whole body of training data. It also allows to overcome some drawbacks of the binary logic. In fact, without verifying the correctness of the parameter value, according to binary logic approach even **if** one value of the parameter exceed the threshold **then** maintenance operations have to be carried out.

An important difference between the two approaches is relevant to the way of taking into account the two considered parameters. In fact, Ecotrack considers SD of alignment and SD of longitudinal level separately; then by linear extrapolation forecasts the dates on which parameters threshold will respectively be reached and assumes as tamping date the closest one by applying a **OR** (logic) rule.

On the contrary, the FIS model consider both the parameters at the same time: it is based on a systemic and multicriteria approach to the parameters values analysis. Thus, a parameters correlation is implicitly assumed. Actually, in order

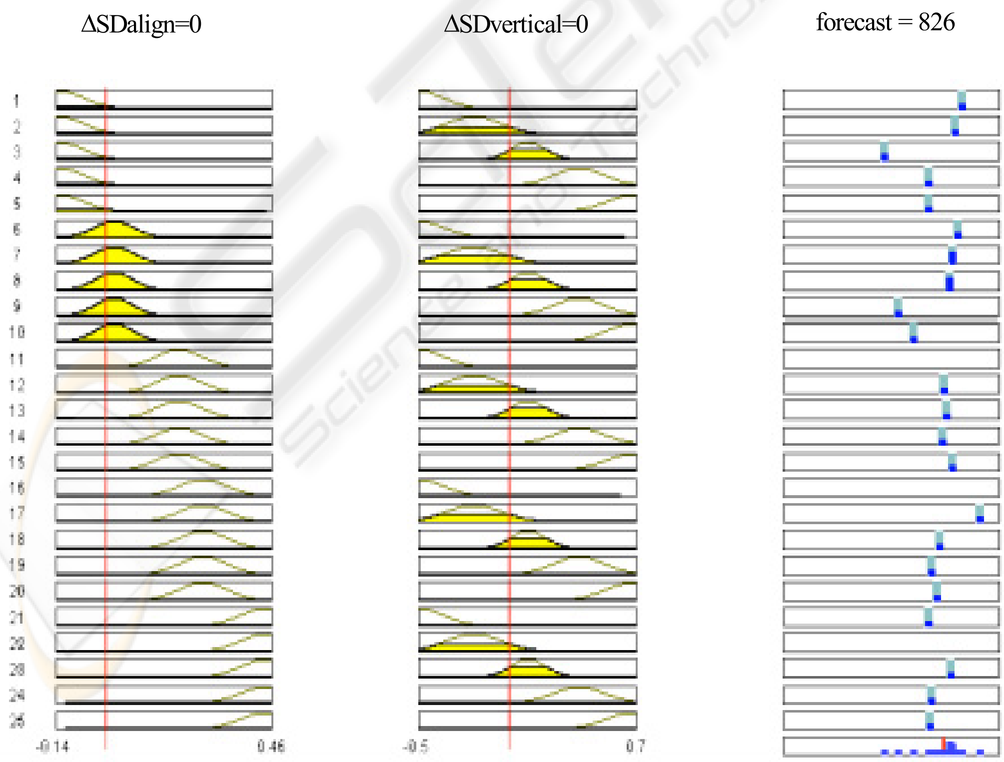


Figure 6: Rules of the fuzzy inference system

to held higher safety level each fuzzy rule assumes the lowest membership degree of the two parameter by means of an **AND** (logic) rule.

For both the approaches a large amount of track technical and geometrical qualitative and quantitative data is needed and usually most of the railways company do not have enough data. Ecotrack assumes the available data within the software database while the proposed FIS system the data are used during the training phase of the ANN and to validate the calibrated model.

Some problem to reach an effective and consistent implementation of such a fuzzy system may occur when there is a lack of data or when the analyst assumes incorrect data as reliable. Actually, under these assumptions rail track analysis is difficult using traditional software too.

Further research will be devoted to improve the proposed DSS. In particular, we will deal with:

– define a hierarchically higher analysis level in order to gather homogeneous maintenance works on adjacent track-segments; to this purpose we are defining a Subtractive Clustering method;
– introducing new rules in order to allow the DSS to carry out analysis when insufficient or incorrect data are available;
– defining time-function of the track quality indexes in order to determine a track deterioration model closer to the theoretical one.

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