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DEVELOPING DETERIORATION PROBABILISTIC MODEL ON THE BASIS OF WEIBULL DISTRIBUTION FOR RAIL WEAR WITH CASE STUDY IN LORESTAN RAILWAY

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Abstract

The vital part of every overall maintenance system is the "predicting future condition" sector. This sector will receive all data which are "gathered by inspection systems and saved in data base" and predict the future condition by analyzing this information.
In this research, after categorizing the rail situation due to rail wear defect index, the suggested Deterioration Model developing on the basis of Weibull distribution is reviewed. The Deterioration Function is defined by Markov Transition Probabilities Matrix. Generally, for all practical uses in railway track maintenance management, the non homogenous models are used. Since today, in all efforts which has been made in the country, rail condition prediction has been based on homogenous models, and casual parameters in deterioration models have not been applied. On the other hand, the most important influencing casual variable on rail wear is the passing traffic. In this research, for solving the deterioration model, only this variable is applied.
Thereafter, the future rail condition on the basis of ten sections which have 200 meters length in Lorestan track that they are placed in curved track with 250 meters radius is reviewed. In fact, by applying the Deterioration Wear Model, and the two "time and line passing traffic" variables, we can predict the future rail situation on six months periods. In addition, the rail durability, from the wear view, can be predicted by Deterioration Model. In this way we can predict that in the inspected area in Lorestan, regarding the analyzed start point date, after six periods of time (three years) the rails of the curved track in the studied area which had 250 meters radius must be replaced.

Keywords: Deterioration model, Markov theory, Rail wear, Rail durability

1 Introduction

There are different methods to estimate the line situation in future. In this research, Markov chain, the most common issue in dealing with maintenance, is selected as rail condition prediction. In this method, Deterioration function is defined by Markov discrete Transition Probabilities Matrix.Markov transition process can be homogenous or non-homogenous.
In homogeneous transition , some casual variables such as traffic loading , environmental factors, Sub grade resistance and etc, are fixed variables in all the analysis period and due to this fact P probability matrix is fixed in all the periods. All the projects carried out in Iran are dealing with track condition prediction on the basis of homogeneous models and casual factors are not being interfered in the deterioration models. For example in a thesis in Sharif University (Reference No.1), a homogeneous model using CTR index to predict track condition is applied. Homogeneous and none-homogeneous models are applied more or less in all

over the world.(see Reference No.[2],[3],[4],[5]). One of projects regarding rail deterioration prediction is an expert project in Australia that develop a model for rail deterioration with rail failure prediction [3]. whereas rail deterioration is not analyzed on the basis of wear .
Regarding the extension of the rail defects and its costly maintenance leading into rail replacement and also the extension of rail wear in great dimensions in Iran Railway track and as just the rail wear is the only source of the database in the network and just measuring this defect is one of the numerous rail defects in Railway of our country being measured by line measurement machine, consequently in this research rail condition prediction is carried out on the basis of its wear. On the other hand, the most important influencing casual variable on rail wear is the passing traffic. With the passing traffic on the rail we will observe more wear. In this research, for the case of simplicity, only this variable is applied in solving deterioration model. The proposed mode of the deterioration is developed on the basis of Weibull distribution and also deterioration function is expressed by Markov discrete Transition Probabilities Matrix.

2 Markov and semi-Markov model

Markov model applies Transition Probabilities Matrix. One transition probabilities matrix is a set of rail condition transition probabilities from one level to another one. The assumption in this method is that the future condition is depending on the current condition and is not based on the system performance in the past. Following Markov chain method, future condition vector, PCS(t),is gained from the rail condition at (t) period and the preliminary condition vector, PCS(0).For example:

$$\begin{aligned} PCS(1) &= P_1 PCS(0) \\ PCS(2) &= P_2 PCS(1) = P_2 P_1 PCS(0) \\ PCS(t) &= P_t PCS(t-1) = P_t P_{t-1} \ldots P_1 PCS(0) \end{aligned} \quad (1)$$

Where P_t is transition probability matrix at time t and PCS(t) is the condition vector at (t) period. PCS lead us to the rail condition quality such as rail wear index or any appropriate scale in the quantitive analysis. All the elements of matrix P_t are transition probabilities. So here all the elements are between zero and one and the sum of the elements of each row equals one.[6]
Semi - Markov model is made by available data and the experience of professional experts in permanent way. The main advantage of this type of model is using mental sources that reduce the need to collect field data. Despite Markov model, these models can predict the future condition from the past condition via transition probability matrix.[7]

3 Deterioration model development

Infrastructure deterioration models are mathematical relationships between a dependent variable, namely deterioration or change in condition, and a set of casual variables including design attributes, traffic loading, environmental factors, age and maintenance history. The main challenge to develop accurate deterioration models for infrastructure facilities is that condition is often measured on a discrete scale. However, facility deterioration itself is a continuous process. For example, in reinforced concrete bridge decks, reinforcing steel bar corrosion is gradual and slow or rail wear is done gradually and over a priod.Furthermore, in the in the initial stages the deterioration processes are not is occurred at either microscopic scale or the subsurface level, so it is not observed directly.Wheras, indicators of performance are being observed. It is therefore necessary, in developing stochastic discrete state deterioration models, to correctly account for both the underlying Unobserved continuous state deterioration process and the observed discrete-state deterioration indicators. [2]
For clarity of presentation and without loss of generality, the model is developed for the simple bi-variate case where the facility can be in one of only two possible states, namely 1 and

0, with the latter state reflecting a poorer condition. Once a facility has undergone a change in state from 1 to 0, then no further changes are possible because condition cannot improve without a rehabilitation activity. In this research it is assumpted that the track is without maintenance. Consequently, only the first part of the sequence ending with the first time that a state of 0 is recorded contains meaningful information. The time variable *t* is set to zero at the time of the most recent rehabilitation, or at the time of structure construction. In other words, at t=0 state 1 is recorded. The value of threshold deterioration *k* reflects the boundary defining the condition states of zero and one. The time at which facilities deterioration level reaches k represents the duration of state 1and is denoted by t=T.

Typically, discrete-time, state-based deterioration models are characterized by transition probabilities for points in time separated by a constant period Δ, which is usually set at one or two years, the commonly employed inspection periods.

The probability of the transition out of state 1 at time *t*, therefore, is the probability of observing the facility having already undergone a drop in state(i.e., change in state from 1 to 0) at time t+Δ conditional on an observed facility state of 1 at time *t*. This conditional probability is denoted by *R* (*t*, Δ) and is given by the following:

$$R(t,\Delta) = \text{prob}\left(t\langle T\langle t+\Delta | T\rangle t\right)$$
$$= \frac{\text{prob}\left(t\langle T\langle t+\Delta\right)}{\text{prob}\left(T\rangle t\right)} = \frac{F(t+\Delta)-F(t)}{1-F(t)} = \frac{F(t+\Delta)-F(t)}{S(t)} \tag{2}$$

Where *F* (*t*) = cumulative distribution function of the duration random variable *T*; and *S*(*t*)=1-*F*(*t*) Which is known as the survival function in the stochastic duration modeling literature. Hence, if *F*(*t*) is known, *R*(*t*, Δ) can be computed for any value of *t* and Δ. In other words, given a time-based model characterizing the probability density function of the duration *T*, the transition probabilities of the corresponding discrete-time, state-based model can be readily determined from *R*(*t*, Δ).

3.1 Hazard rate function

The probability of the transition out of state 1, *R*(*t*, Δ), clearly depends on the period Δ. The larger the value of Δ, the higher the probability and vice versa. Therefore, it is convenient to construct a measure that reflects the average rate at which the transition out of a state will occur by dividing this probability by Δ.This measure is represented with $\lambda(t)$.

If the facility is monitored almost continuously (i.e., successive observations are taken at very short intervals), then the conditional probability of Eq. 2 divided by Δ reduces to the following:

$$\lambda(t) = \lim \frac{R(t,\Delta)}{\Delta} = \lim \frac{F(t+\Delta)-F(t)}{\Delta.S(t)} = \frac{f(t)}{S(t)} \tag{3}$$

Where *f* (*t*) =probability density function (PDF) of *T*.

In other words, based on Eqs. (2) and (3), the probability of a transition out of state 1 at time *t* over an infinite small period Δ=*dt* is $\lambda(t).dt$. The function $\lambda(t)$ is known as the hazard rate function in the stochastic duration modeling literature and reflects the instantaneous rate (or risk) at which a facility will transition out of its current state to the lower state after time *t*.

3.2 Duration Model Specification

The functional form of the hazard rate function, ($\lambda(t)$), allows for a convenient interpretation of the nature of the phenomenon being modeled.[2]. A constant hazard rate function implies

a process where the conditional probability of the transition out of the state -given by Eq(2)- does not vary over time. This implies that no matter how long the time spent in a state might be, the probability of the transition out of that state remains constant and hence independent of that time. This reflects a process lacking memory, and it can be shown that the associated distribution of the duration *T* follows the exponential PDF. Such a characteristic is referred to as duration independence. A hazard rate function that is monotonically decreasing over time implies that the probability of the transition out of the state decreases with an increasing time spent in that state. Conversely, a hazard rate function that is monotonically increasing over time implies that the probability of the transition out of the state increases with an increasing time spent in that state. These characteristics are referred to as negative and positive duration dependence,respectively; see Greene (1997) For more detail on all three characteristics.[8]
As pointed out earlier in this section, once the PDF, $f(t)$, of the duration *T* is known, the transition probabilities of the corresponding discrete-time, state-based models can be determined. Therefore, all that remains to complete the development of the methodology is the specification and estimation of $f(t)$. Given the intuitive interpretation of the hazard rate function, ($\lambda(t)$),and its straightforward relationship with the probability density and survival functions given by Eq. (3), it is both convenient and appealing to specify the hazard rate function directly. Once this function is estimated, the PDF of duration can be determined, and consequently the transition probabilities can be readily computed. Although material aging and fatigue imply that infrastructure deterioration is in general expected to follow a monotonically increasing hazard rate function(reflecting positive duration dependence), in estimating such a model it is desirable to adopt a single functional form that can cover the spectrum of negative duration dependence, duration independence, and positive duration dependence. such functional form corresponds to the duration *T* following the Weibull PDF. The hazard rate function associated with the Weibull PDF is given by the following:

$$\lambda(t) = \lambda P(\lambda t)^{P-1} = P\lambda^{P} t^{P-1} \tag{4}$$

Where P, λ = parameters to be estimated.

Depending on the value that *p* takes, the process falls in one of the three duration dependence categories. If 0‹*p*‹,1, then $\lambda(t)$ is monotonically decreasing and reflects negative duration dependence. If p=1, then $\lambda(t)$ takes the constant value of λ and reflects duration independence, or lack of memory, where the Weibull PDF reduces to the exponential PDF. And if *p*›1, then $\lambda(t)$ is monotonically increasing and reflects positive duration dependence.
It is useful to point out that this explicit treatment of state duration in modeling deterioration reflects a special case of the Semi-Markov process. Such a process does not possess the Markovian property due to the presence of duration dependence unless the Weibull PDF takes the form of the exponential PDF. In this special case, the semi-Markov process reduces to a continuous-time Markov chain, where duration independence holds.
As already discussed, infrastructure deterioration depends on a set of causal or explanatory variables. Clearly, the Weibull hazard rate function of Eq. (4) does not reflect the effect of such variables. Although this is a serious limitation of this model, its extension to include these variables can be achieved simply through the replacement of the constant parameter λ with a function dependent on the relevant variables.To ensure that this function is strictly positive, the following exponential specification is adopted:

$$\lambda = e^{-BX} \tag{5}$$

where X=column vector of casual variables (which includes the value one to capture the constant term):in the rail wear model , as the most important casual variable effective on the rail wear is passing traffic, X is only including one variable and that is the passing traffic. So X vector is turned into a number and β=row vector of parameters to be estimated: in wear model as X vector is a number, β vector is number either that is resulted from drawing exponential diagram of rail wear breakout index to the passing traffic. Combining Eq. (4) and Eq. (5) results in the following variable-dependent hazard rate function:

$$\lambda(t) = e^{\beta x} \quad p(e^{-\beta x} t)^{p-1} = p e^{-p\beta x} t^{p-1} \tag{6}$$

Under this more general specification, therefore, the duration is now a function of the values of *p* and X. Note, however, that the nature of duration dependence is still strictly dependent only on *p*.

3.3 Transition Probability Determination

As already discussed, once the duration model is estimated, the transition probabilities of the corresponding discrete-time, state based model can be computed. In effect this amounts to determining the transition probabilities of a discrete-time, state-based process from an estimated semi-Markov process where time is continuous. In the bivariate case the probability of the transition out of state 1, which is given by $R(t,\Delta)$ of Eq. (2), is simply the probability of the transition from state 1 to state 0. Consequently, the transition probability from state 1 to state 1 is $1-R(t,\Delta)$. Under the specification of Eq. (6), where a Weibull PDF and the presence of casual variables are assumed, the probability of remaining in the same state, denoted by $P1{,}1$, is given by the following:

$$p_{1,1} = 1 - R(t,\Delta) = \frac{\exp\left[-\lambda^p (t+\Delta)^p\right]}{\exp\left[-(\lambda t)^p\right]} \tag{7}$$

And the probability of the transition from state 1 to state 0, denoted by $P1{,}0$, is given by the following:

$$p1{,}0 = R(t,\Delta) = 1 - \frac{\exp\left[-\lambda^p (t+\Delta)^p\right]}{\exp\left[-(\lambda t)^p\right]} \tag{8}$$

In Eqs (7) and (8), λ is as given by Eq. (8). Thus, given an estimated Weibull hazard rate function of Eq. (6), the transition probabilities for the bivariate case can be computed based on Eqs. (7) and (8) for any point in time *t* and any period Δ.

For the multivariate case, the three-state scenario is considered. A duration model for each state is developed exactly as discussed under the bivariate case. In this discussion, the three states are denoted by 2, 1, and 0 whereby the additional state 2 is introduced reflecting the situation where state 2 is the best condition state and 0 the poorest. In this scenario the remaining elements of transition probability matrix are as followings:

$$p_{2,2} = 1 - R_2(t,\Delta) = \frac{\exp\left[-\lambda_2^{p2} (t+\Delta)^{p2}\right]}{\exp\left[-(\lambda_2 t)^p\right]} \tag{9}$$

$$P_{2,1} = P_2 \lambda_2^{P2} \exp\left[(\lambda_2 t)^{p2}\right] \times \int_t^{t+\Delta} T^{p2-1} \exp\left[-(\lambda_2 t)^{p2} - \lambda_1^{p1} (t+\Delta-T)^{p1}\right] dT \tag{10}$$

$$P_{2,0} = 1 - P_{2,2} - P_{2,1} = R_2(t,\Delta) - P_{2,1} \tag{11}$$

where $R_i(t,\Delta)$ = probability of the transition out of state *i*; λ_i =given by Eq. (5)for state *i*; and

P_i= parameter *p* of Eq. (6) for state *i*.
As in the bivariate case, the transition probabilities for the three state multivariate cases can be computed based on Eqs. (9), (10), and (11) for any point in time *t* and any period Δ. The extension of the above derivation to the case of more than three states follows a similar treatment.

4 Case study of Lorestan Railway

To investigate the efficiency of the proposed model, it is tested on one of the lines in Iranian railways network. To do this, Lorestan districts is selected due to the problematic rail condition and the presence of numerous Curves. The passing traffic from this district is mostly of freight type and it has U33 rail. One of the most prominent features of this district is having a lot of curves with small radius causing more rail wear [11].
To make the theory more simple and as the most influensive casual variable on rail wear is passing traffic, it is applied as the only variable in this paper. Besides, to measure rail wear in this district, the data of Line measuring machine, EM120, measuring the rail profile by none contact system in per m,is applied. Here the data of three periods with the interval of 6 months Δ = 0.5 are existing. The first period is on February 4, 2007, the second period is the next 6 months and respectively the third period is about 1 year later.
As the most amount of wear is occurred in the curves namely, curves with small radius, in this research 2km of this district located at the curve with 250m radius is selected as the case study. The most amount of the wear in the curves are lateral type of wear. Besides, in the curves with low passing speed (regarding the freight traffic) the wear is occurred on the interior rail so, this paper focus on lateral wear of the interior rail in each curve. Also according to the balastic lines superelevation technical and general features in Islamic Republic Railway Of Iran , the maximum allowable lateral wear for a line with the speed of 60km/h (D classification)and with U33 rail, is 15mm.[9]
Passing traffic in this district used as model development in 7 years (every year is meaningful from March 21 to the next March 20), from March21, 2001 with the growth rate of 6% to March 20, 2008 is shown in table 1.[10]

Table 1 The annual passing traffic of Lorestan

Year	1	2	3	4	5	6	7
Annual passing freight (1000 ton)	2542	2680	2860	3018	3198	3389	3593

To solve the model, the passing traffic from the studied district in each period is required starting from one starting point. So, March 21, 2006 is considered as the traffic basis and the passing traffic is gained from it in each period.
Searching the freight and passenger performance bill of lading in railway, it was defined that the most part of passing traffic in Lorestan is of freight traffic and also due to the volume of the passing traffic near the district capacity, the traffic change rate monthly is fixed, this value is 1 in this paper. Then, according to table(1) and the monthly traffic change rate, the passing traffic is computed in each period.

4.1 The index applied in model solution and lines classification

The condition index is a number computed from an equation and is applied to express the track condition and it can express the level of line servicing amount. If the condition index is measured in definite exploitation period, the empirical deterioration function of each index is determined via the condition index diagram against passing Tenaj.This function is of great importance in tracks maintenance management. The index applied to shown rail condition and is used in this paper can define the amount of rail service. The index is denoted by γ and is defined by the relation of two areas. If we draw a diagram of wear amount (vertical axial on mm) to kilometer (horizontal axial on m), the area under the diagram is displayed by S_W.Then the following equation express obviously the definition of this index:

$$\gamma = \frac{S_W}{S_M} = \frac{\Sigma Y}{S_M} \tag{12}$$

Where, S_W=the area under the wear amount diagram to the distance and as the EM120 machine measures the wear data in per m, So the wear amount (Y) is existing per 1m.Then, the area under the diagram is the sum of wear in 50 points in 50m parts and $S_{M=}$ the area of allowable wear = lateral allowable wear (15mm) × part length (50m).
Two kilometers of the selected area in Lorestan is consisting of 10 parts of 200m that all of them belong to the curves with 250m radius. (Some of the parts next to each other and in one curve and the others are in different curves), then each part itself is divided into four parts with 50m longitude. Applying the following definition for the index, at first the index in each 50m part for every period of machine scan is measured and then is gained from the average between 4 parts, the rail wear defect index for each 200m part in each measurement period. Thus, for every 200m part, 3 indexes of 3 measurement periods are available.
To determine the lines quality, the classification of the lines is done by γ index. This classification is done in table (2):

Table 2 The classification of the lines on the basis of γ index

The scope of γ index	$0.25 > \gamma > 0$	$0.75 > \gamma > 0.25$	$0.75\ \gamma >$
Quality title	Good	Average	Weak
Rank	2	1	0

Besides, if the average wear amount (here 50 points) exceeds the allowable wear boundary (15mm), that part is located on poor condition. In this ranking, rank 2 is the best state and 0 is the worst one.

4.2 The determination of hazard rate function $\lambda(t)$

To achieve λ, the exponential diagram should be drawn between γ index and passing traffic. The resulting cure equation is the same λ equation with traffic (x). According to 10 parts with 200m long, 10 equation for λ is gained on traffic. On the other hand for three cases scenario as the case study of this research (3 stage good, average, poor with 3 ranks 0,1 and 2), we need λ_i (λ for state i in which i = 0, 1 ,2). As it is not possible to go out of stage 0 or poor state, and there is not any worse state than it, so the survive probability in this state is 1 after one period. ($P_{0,0}$=1) Consequently, just λ_1, λ_2 should be found. Among 10 equation for λ it was observed that 5 case is about out of state 2 and 5 cases are about out of stage 1. On the other hand, 5 equaitons for λ_1 and five equations for λ_2 were achieved. Of 5 equations, we should select the one fitted with high accuracy and its R_2 more near to 1 and it can be selected.
Thus, selected λ_1, λ_2 that are respectively related to the ninth and fifth part, are gained as:

$$\begin{aligned} \lambda_1 &= 0.379e^{0.155X} \\ \lambda_2 &= 0.099e^{0.282X} \end{aligned} \tag{13}$$

There is another parameter as p in hazard rate function. As it was said before, as the wear rate change over the time is not very tangible, here $P_i = 1$ showing the duration time independence state or memory loss and get weibull PDF of exponential PDF form. By having λ_i, $P_{i,}$ $\lambda(t)$ is easily achieved and is applied for transition probability matrix in each period. The following is about the computation of every transition matrix element in each period. Then, rail wear condition is predicted in 6 month period.

4.3 Transition probability matrix determination

In Excel software, the elements are one by one found after preparing one Spirit sheet and giving some inputs such as x(passing traffic)and t(time) and Δ(duration of time).Transition probability matrix p for the first 6 month is as followings:

$$P = \begin{bmatrix} 0.89 & 0.10 & 0.01 \\ 0 & 0.74 & 0.26 \\ 0 & 0 & 1 \end{bmatrix}_{3\times3} \quad (14)$$

If at the analysis staring time (t=0), rail is in good condition, rank2, it can be predicted by this matrix that according to Equ.(15), the next 6 months, rail is 89% is remained in good condition, 10% change to average stage and 1% to poor state. Once the highest probability is the starting point, it can be predicted that rail wear is in good condition after 6 months.

$$p(t=0) = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}$$

$$p(t=0.5) = p(t=0) \times P(t=0)_{3\times3} \quad (15)$$

$$p(t=0.5) = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \times \begin{bmatrix} 0.89 & 0.10 & 0.01 \\ 0 & 0.74 & 0.26 \\ 0 & 0 & 1 \end{bmatrix}_{3\times3} = \begin{bmatrix} 0.89 & 0.10 & 0.01 \end{bmatrix}$$

$P(t)_{3*3}$ is the transition probability matrix in each period.
In the next stage, transition probability matrix p is achieved for the second 6 months as:

$$P = \begin{bmatrix} 0.85 & 0.14 & 0.01 \\ 0 & 0.69 & 0.31 \\ 0 & 0 & 1 \end{bmatrix}_{3\times3} \quad (16)$$

It should be considered that condition vector at t is the starting vector for the next chain that is different from a transition matrix.Thus,if at (t=0.5) the resulting condition of the first 6 months is considered as the preliminary condition for the second 6 months in this case of at the beginning of the second 6months rail is in good condition, rank 2, through this matrix and if it is the highest probability , it can be predicted that after the second 6 months or one year after the analysis the rail wear remains in good condition.

$$p(t = 0.5) = \begin{bmatrix} 0.89 & 0.10 & 0.01 \end{bmatrix}$$

$$p(t = 1) = p(t = 0.5) \times P(t = 0.5)_{3\times3} \qquad (17)$$

$$p(t = 1) = \begin{bmatrix} 0.89 & 0.10 & 0.01 \end{bmatrix} \times \begin{bmatrix} 0.85 & 0.14 & 0.01 \\ 0 & 0.69 & 0.31 \\ 0 & 0 & 1 \end{bmatrix}_{3\times3} = \begin{bmatrix} 0.76 & 0.19 & 0.05 \end{bmatrix}$$

Thus, by passing traffic and the required time, with 6 months accuracy, rail wear condition is predicted.

4.4 The estimation of rail age on the basis of wear

If the mentioned trend in article 4–3 is continuing in the next periods and a good approximation of rail age in curve with 250 m radius is found. We should consider that two parameter, time and passing traffic, should be defined. The value of ranking traffic in each period is gained by the 6% growth rate.Time parameter (*t*) in each period is gained in each period by adding 6 month or half a year to the previous period. To get the rail age, this cycle is continued to the extent that the rail by considering the highest probability is located on poor condition.
In the final stage, transition probability matrix *P* for the sixth (six months) and the condition vector at the end of the sixth period is as followings:

$$P = \begin{bmatrix} 0.38 & 0.61 & 0 \\ 0 & 0.38 & 0.62 \\ 0 & 0 & 1 \end{bmatrix}_{3\times3} \qquad (18)$$

$$p(t = 3) = \begin{bmatrix} 0.08 & 0.26 & 0.66 \end{bmatrix} \qquad (19)$$

According to Equ.(19) in the investigating zone in Lorestan district and in the rails with curves, 250m radius by considering the analysis starting time after about 6 period or 3years, rail is in poor condition. It means that in February 2010 the rails on the studied zone with 250m radius should be changed.

5 Conclusion

Applying the proposed model, rail wear condition is achieved with any passing traffic and at any time. In the case study this process was done for the rail located on the curve with 250m radius at the period of 6 months.Indeed, by having passing traffic and the required time, with the accuracy of 6 months the rail wear condition is predicted. On the other hand, by this method rail age is predicted and the time to replace the rail is estimated. To achieve the rail age the calculation cycle should be repeated to the extent that rail is located in the poor state by considering the highest probability. By solving the case with the above method, in the studied zone in Lorestan district and the rails located on the curves with 250m radius by considering analysis starting time after 6 periods or 3 years, the rail is being located on poor state and it should be replaced. Thus, rail state can be predicted in the future years for the other lines in the country and their wear limit is estimated. On the other hand rail age is estimated and the exact time of its displacement is determined.
It is worth to mention that due to 3 periods of rail wear information in the country's tracks in this research hazard rate function is just being fitted by 3 points. In the case of using the

information of the more periods, accurate results are achieved. Besides; the proposed model is applied in the prediction of the other line components and the right of the other structures.

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