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A Simple State-Based Prognostic Model for Railway Turnout Systems

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***Abstract* – The importance of railway transportation has been increasing in the world. Considering the current and future estimates of high cargo and passenger transportation volume in railways, prevention or reduction of delays due to any failure is becoming ever more crucial. Railway turnout systems are one of the most critical pieces of equipment in railway infrastructure. When incipient failures occur, they mostly progress slowly from the fault free to the failure state. Although studies focusing on the identification of possible failures in railway turnout systems exist in the literature, neither the detection nor forecasting of failure progression has been reported. This paper presents a simple state-based prognostic method that aims to detect and forecast failure progression in electro-mechanical systems. The method is compared with Hidden Markov Model based methods on real data collected from a railway turnout system. Obtaining statistically sufficient failure progression samples is difficult considering that the natural progression of failures in electro-mechanical systems may take years. In addition, validating the classification model is difficult when the degradation is not observable. Data collection and model validation strategies for failure progression are also presented.**

***Index Terms*—Fault Diagnosis, Diagnostic expert system, Failure Analysis, Rail transportation maintenance, Forecasting, Prognostics, Remaining useful life estimation, Railway Turnouts, Time Series**

NOTATION

ϕ : Constant in exponential degradation model

β : Random variable following s-normal distribution

μ_β : Mean of β

σ_β^2 : Variance of β

λ : HMM Model

π : Initial probabilities of HMM

$A_{i,j}^l$: Transition probability from state i to j in level l

B : Observation probability distributions

CH : Calinski-Harabasz cluster validity index

n_c : Number of samples clustered in cluster *c*

z_c : Center of cluster *c*

z : Center of all clusters

x_i : Time series data sample *i*

k : Number of clusters

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I. INTRODUCTION

It is now an obligation to improve reliability, availability, and safety of railway systems to accommodate increasing passenger and cargo transportation with higher train speeds, greater axle loads, and increased service frequency. According to a report of the European Commission, the passenger and cargo transportation volume in European railways are expected to double and triple respectively in 2020 [1]-[5]. It is obvious that this demand increase cannot be satisfied with only building new railways; the efficiency of existing and new railways should be increased. This could be achieved with minimum cost by increasing the availability of railways, which is directly related with repair and maintenance frequency.

Britain's railway infrastructure operator, Network Rail, was responsible for approximately 14 million minutes of train delay in 2002-2003, costing approximately 560 million GBP [5]. Railway turnout systems are the main component of railway infrastructure that affects the availability of the system [6]. For example in England, 3.4 million GBP is spent every year for the maintenance of turnout systems for 1000 km of railways [6]. Condition-Based Maintenance (CBM), in which the health of the machine is observed in real time and maintenance decisions are based on the current and forecasted machine health, increases system availability, reliability and safety while reducing operating and support costs [7]-[8]. Thus, the application of CBM on railway turnout systems has critical importance for increasing the efficiency of railways.

Diagnostics and prognostics are the two main components of CBM [7]. Diagnostics, the process of identifying the failure, is basically a classification problem; prognostics, the prediction of the failure time of the component with an incipient failure, is a forecasting problem. Various diagnostic methods have been presented in the literature for many diverse industrial systems [9] - [14]. Diagnostic methods on various components of the railway and train have also been reported [15]-[20].

There are three main approaches in the literature for diagnostics on turnout systems: feature-, model- and empirically-based methods. In the first approach, special features that help to identify the failures are defined. For example in [21], three features (i.e., irregularity, location of maximum point, and symmetry) are defined in the time series data. These features are obtained by analyzing the absolute difference between the reference and actual signals. The reference signal is collected from a fault-free system. The absolute difference is in the form of a time series-like reference. Irregularity is defined as an unexpected bump in the absolute difference. The location of the maximum point is compared with the maximum point location in the reference data. The symmetry of the absolute difference of the left and right sides of the maximum point location is used as the third feature.

In model-based approaches, a model is defined to characterize the system. Deviation from the model is defined as failure and identified as the difference between the model outcome and actual data. Various methods may be applied. In [22], the unobserved component model, in which an observable variable is written as a function of several unobservable components, is used. In [23], parameters like velocity and air volume are expressed as polynomial functions of pressure in a pneumatic turnout system. Thus, the difference between the actual velocity and/or air volume and their expected values for a given pressure identifies the failure.

In empirically-based approaches, a fault-free sample is considered as a reference signal, and failures are identified based on the resemblance of a given signal to the reference signal. The Kalman filter is used in [24] for noise removal and failure identification based on a reference signal. Ref. [25] presents an expert system for failure identification using resemblance to the reference signal. The resemblance is quantified using simple Euclidian distance and dynamic time warping approaches. A good review for failure detection methods for railway turnouts is given in [26].

Failure diagnosis is an important task; however, it only aims to stop (and schedule a maintenance/repair) the system when a failure is identified or let the system continue to work otherwise. Incipient failures progress slowly [27]. This progression starts from the fault free state and ends at the failure state [28]. The system functions properly and does whatever is expected (albeit maybe with decreasing efficiency) until reaching the failure state. It is obvious that the detection of failure progression is more valuable than its detection after the failure reaches to a point. In addition, it is a prerequisite for prognostics [28], [29].

Studies of prognostics for different systems have appeared in the literature in recent years. Prognostic methods can be separated into three categories: evolutionary, degradation prediction, and state-based prognostics [8]. Evolutionary prognostics involves trending features until a predefined threshold, whereas the degradation calculated with features is predicted with statistical and computational methods in the degradation prediction based prognostics [8]. In the last category, the states representing the failure progression are detected and forecasted.

Hidden Markov Models (HMMs) have been used as state-based prognostics in [28], [30]-[34] with different application areas such as drilling processes, pump systems, and AC motors. The life of a drill-bit is represented by health states, each of which is modeled as a single HMM in [31]-[32]. Health state of a drill-bit is identified with the HMM with highest likelihood value given the observed time series signal. In standard HMM, transition from one state to another is independent of time spent in the current state. This assumption is not true in failure degradation applications and it is relaxed in [30] with semi-Markov concept.

In [28], health states are represented as the top state of Hierarchical HMM, rather than a distinct HMM as in [28], [31], [32]. Monte-Carlo simulation with health state transition probabilities is used in [28] to calculate the remaining useful life (RUL). In [33], frequency and severity of noncatastrophic faults are used to detect RUL of an electric drive. Four methods have been used for fault detection and HMM based framework is presented for prognostics. Second order HMM, in which states depend on the two previous states, is used for prediction of health states in [34]. In [35], concentration of lubrication samples is used to identify the abnormality in diesel engines. Then, a belief network created with expert knowledge is used for prognostics.

This paper presents a simple state-based prognostic (SSBP) method that aims to detect and forecast failure progression in electro-mechanical systems. The method is compared with HMM-based methods using real data collected from a railway turnout system. Failures in electro-mechanical systems mostly occur slowly, and it may take months/years for a failure to occur. Thus, obtaining statistically sufficient samples from the fault-free state to the failure state may require a very long time. In addition, the validation of classification methods requires knowing the real failure progression states. However, observing the real failure progression states is very difficult, if not impossible, in most systems [28]. This paper also presents a solution to these problems. The main contributions of this paper can be summarized as follows:

1. Presenting a simple state-based prognostic method and its comparison with HMM-based prognostics;
2. Application of presented (SSBP) and HHM-based prognostics methods in a railway turnout system;
3. Presenting a data collection strategy for slowly developing failures to model the real failure progression;
4. Proposing a strategy to validate the state estimation method without knowing the real failure progression states.

The organization of the paper is as follows: section II gives the details of a turnout system, section III presents the modeling structure, section IV gives experiments and results with real data collected from a turnout system, and section V concludes the paper.

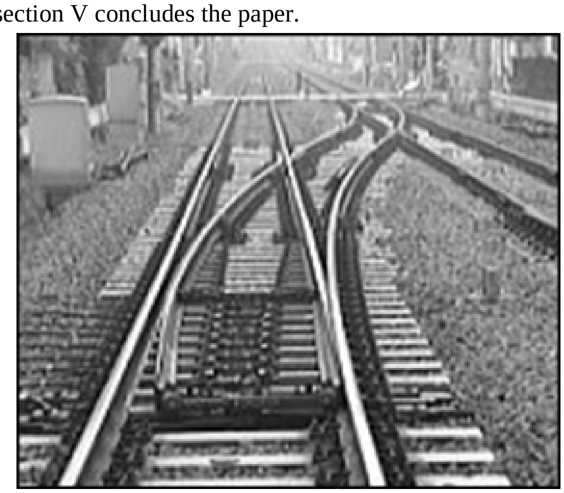


Fig. 1. Railway tracks to be moved by a turnout system

II. RAILWAY TURNOUT SYSTEM

Railway turnout systems allow trains to change their tracks by moving the rails before the train passes, as seen in Fig 1. The turnout system, which is a form of single throw mechanical equipment, is run by a motor as shown in Fig 2. There exist different types of railway turnouts based on motor working principle, such as electro-mechanic, hydraulic, and pneumatic. The motor moves the blades/switches in two directions, called normal and reverse. This movement takes several seconds. Once the movement is completed, the switches are locked in their position. It is claimed that the turnout systems are the one of the most important component of the railway infrastructure, and there exist examples of accidents caused by turnout failure [6]. This paper focuses on electro-mechanic turnout systems, which consist of a motor, reduction gear, several bearings, drive-detection rods, switches etc.

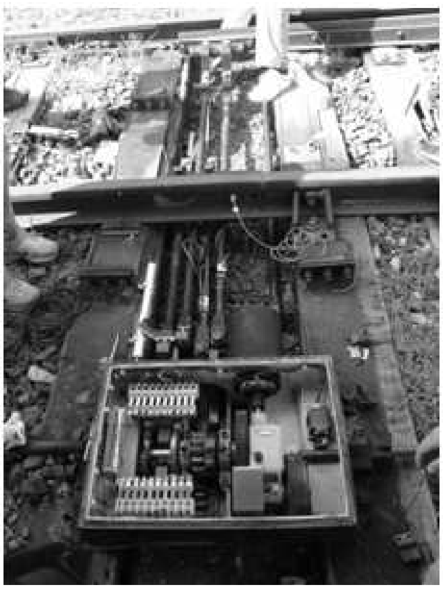


Fig. 2. A railway turnout system

III. MODELING STRUCTURE

This section includes two sub-sections: failure progression modeling and a simple state-based prognostic method.

A. Failure Progression Modeling

Electro-mechanical failures mostly occur slowly, following a degradation path [36]. It is easy to understand the difficulty of obtaining statistically sufficient failure progression samples, considering that a failure may progress for several months to years in real systems. There are two ways to overcome this problem: 1) using prototypes for data collection or 2) creating the failure progression unnaturally.

The prototypes are created with vulnerable materials, and operating conditions are set so that the failure progresses faster than normal [28], [31]-[32]. Choosing thin drill-bits or preventing the proper functioning of cooling systems are some examples used in the literature [28]. Although this approach may be applicable for simple components like a drill-bit, it is difficult to obtain an acceptable prototype to represent something complex like a turnout system. In such a complex system, the failure progression should be created unnaturally.

The exponential degradation model for systems with no prior information about degradation presented in [36] is used in this paper and formulated as in (1). The degradation paths for samples as shown in Fig. 3 are obtained using this formula. Then, the failure time is defined as the point where the degradation reaches a threshold, providing various lifetimes for multiple turnout systems. The degradation level is divided into several groups as illustrated with dashed horizontal lines in the figure. Each group is defined as a state in the failure progression. The time spent in a state corresponds to the length of the x-axis (time) of the degradation path (signal) when the y-axis falls in that state.

$$S(t_i) = \phi e^{\left(\beta t_i + \varepsilon(t_i) - \frac{\sigma^2}{2}\right)} \tag{1}$$

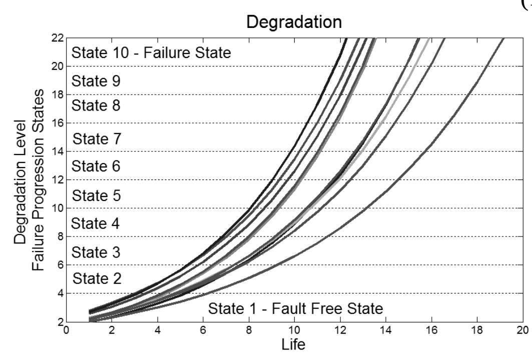


Fig. 3. Failure degradation and discrete health states

After obtaining the life and the time spent in each state for all samples, the data can be collected by creating the failure progression states unnaturally. This could be the size of a crack, how loose a screw has become, the level of wear and tear, or dryness level in the slide chair of the turnout system. When the failure progression is created unnaturally, the data that can be used as representative of that state in different turnout systems, are collected.

B. Simple State-Based Prognostics Method

The presented method (SSBP) includes three steps, as illustrated in Fig. 4: clustering, cluster evaluation, and expected RUL calculation. For clustering, data from the different health states of multiple systems are clustered using any clustering method. k-means clustering is used in this paper due to its simplicity and effectiveness. However, SSBP is independent of the clustering method.

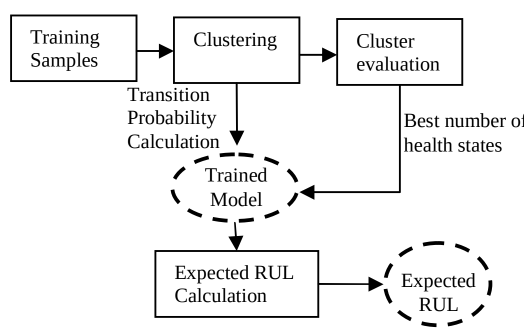


Fig. 4. Prognostics steps

In clustering, the best number of clusters for the given dataset should be identified. In k-means clustering, the number of clusters (k) should be given. Although in classification problems parameters can be optimized using classification accuracy, clustering problems require different evaluation parameters because the real number of clusters and samples that belong to real clusters are not known. Several cluster validity indexes have been proposed in the literature [37],[38]. Silhouette, Davies-Bouldin, Calinski-Harabasz, Dunn, C-index, Krzanowski-Lai, and several other indexes are implemented, and Calinski-Harabasz (CH) is chosen as the most robust one for the dataset used in this paper. The formulation of CH indexes is given in (2).

$$CH = \left[\frac{\sum_{c=1}^{k} n_c \left\| z_c - z \right\|^2}{k-1}\right] / \left[\frac{\sum_{c=1}^{k}\sum_{i=1}^{n_c} \left\| x_i - z_c \right\|^2}{n-k}\right] \tag{2}$$

The cluster validity index gives the optimal number of clusters and health states in our problem. In a failure progression problem, it is very difficult, if not impossible, to observe the health states the system goes through and to know their total number. Thus, clustering and validity indexes are used to identify the number of health states.

After the current health state of a given system is identified using clustering, the remaining useful life is forecasted as illustrated in Fig. 5. The expected RUL is calculated using the transition probabilities between health states as shown (3). The transition probability is the probability of the current health state to change. The results of the *k*-means clustering are used to identify these probabilities. *k* number of clusters and the number of transitions from one cluster to another are found with all training samples. For example, assume three turnout systems with health states numbered sequentially from 1 to 4 (from the brand new to the failure state) as shown in Table 1. Each row shows the progression in health states for a turnout system. The three turnout systems fail after 13, 10, and 9 time units. A total of twelve transitions from state 1 (transition to state 2 after 4, 6, and 2 time steps, state 1 otherwise) have happened in three turnouts. Because three state transitions out of twelve from state 1 have happened to state 2, the transition probability from state 1 to state 2 is initialized as 3/12. Similarly, the state transition probability from state 1 to state 1 (state 3) is initialized as 9/12 (0/12). Other transition initialization values are calculated similarly.

The current health state of the system is represented by h_c in (3) and is obtained using the clustering method. Note that the ∞ in the formula is represented as the RUL upper limit in the SSBP. As the upper limit increases, the approximation of the RUL improves. The probability of the RUL of each value between 1 and the RUL upper limit is calculated one by one. For a given RUL, there exist many different combinations of possible health states. For example, if the RUL is given as 5 with 3 health states, the combinations are as follows: 3 1 1 (i.e., 3 time unit in state 1, and 1 time unit in state 2 and state 3), 2 2 1, 2 1 2, 1 3 1, 1 2 2, and 1 1 3. The number of combinations increases exponentially with the number of health states. To handle the computations, transitions are only allowed from a health state to itself or to a consecutive state. Thus, a state cannot jump to second, third, and so on, consecutive health states directly. The probability of staying in a health state n for st_n times means that the health state transitions to itself $st_n - 1$ times and transitions to the consecutive health state one time. The calculation is given in (6).

$$\left[RUL \mid st = h_c\right] = \sum_{i=1}^{\infty} i \times P\left(rul = i \mid st = h_c\right) \tag{3}$$

$$P\left(RUL = i \mid st = h\right) = \prod_{n=h}^{fail} P\left(stay_n = st_n\right) \tag{4}$$

$$\sum_{n=h}^{fail} st_n = i \tag{5}$$

$$P\left(stay_n = st_n\right) = q_{n,n}^{st_n - 1}\left(1 - q_{n,n}\right) \tag{6}$$

The Monte Carlo simulation with HMM used in [28] does not make the assumption of transition of a state only to itself or the consecutive state. However, SSBP removes some of the complications of HMM. The results of SSBP are compared with those of HMM-based prognostics in section IV. The following subsection discusses the details of Hierarchical Hidden Markov Models (HHMM).

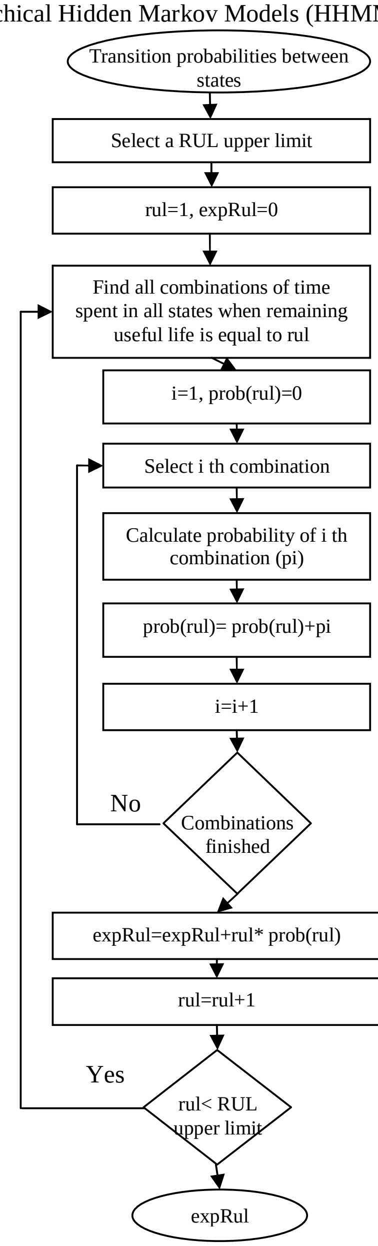


Fig. 5. Flow chart of RUL calculation

C. Hierarchical Hidden Markov Model

The Hierarchical HMM (HHMM) is a version of the Hidden Markov Model (HMM) designed to model hierarchical structures for sequential data. The simplest HHMM includes two hidden layers; the state in the top hidden layer is considered to be a self-contained probabilistic model. In other words, in the simplest HHMM, each state in the top layer is itself an HMM. The observed state is affected by both nodes in the top and low hidden layer in any given time frame. The states in the top hidden layer represent the health states of the turnout system, whereas states in the low hidden layer represent the state of the movement of the rails. In other words, the low level states show the location of the rail during the back and forth movement of the rail. Readers are referred to [8] and [28] for the details of HHMM.

Initialization of HHMM

An HHMM model is represented as λ ($\lambda = (A, B, \pi)$) and includes parameters of initial probabilities (π), transition probabilities (A), and observation probability distributions (B). The following paragraphs discuss the initialization of parameters in an HHMM.

Initial probabilities (π) exist for two hidden variables: top and sub-hidden states. Top hidden states represent the health state of the turnout system. The initial probability of a top state is the probability of a turnout system to be in a given health state for the first usage or after maintenance/repair. This is always 1 for a brand new state (and also after maintenance assuming perfect maintenance) and 0 for other states. The data collected during the movement of the rails with force generated by the turnout system is in the form of a time series and consists of several states (i.e., sub-states). The initial probability of a sub-state is the probability of sub-states in the beginning of the movement. In our experiments, the initial probabilities are assumed to be 1 for the first top and sub-states and 0 for the other states. That is, the perfect maintenance assumption is made, and all turnout movements are assumed to start from the same sub-state.

	Life of turnouts												
	1	2	3	4	5	6	7	8	9	10	11	12	13
Turnout1	1	1	1	1	2	2	2	3	3	3	3	4	4
Turnout2	1	1	1	1	1	1	2	3	3	4			
Turnout3	1	1	2	2	2	2	3	3	4				

Table 1. Turnout health states progression examples

The top state transition probabilities are initialized using the transition probabilities obtained using *k*-means clustering as discussed above. The other transition probability parameter is the probability of the current sub-state to change. To initialize this parameter, the time series data collected during the rail movement are divided into equal number of successive groups: s that also is the number of sub-states. Then $A_{i,j}^{2}$ is initialized as follows: $A_{i,i+1}^{2} = 1/s$, $A_{i,i}^{2} = 1 - 1/s$, and $A_{i,j}^{2} = 0 \quad \forall i, j$ $i \neq j$ and $j \neq i+1$.

The last parameter to be initialized is the observation probability distribution parameter, $B_{i,j}$, which represents the distribution parameters of the observed parameter under health state i and sub-state j. To initialize $B_{i,j}$, the data points that are collected from a turnout system with each health state and sub-state are categorized. The data from all of the $h \times s$ categories are obtained, where h and s are the number of health and sub-states, respectively. Then, the distribution parameters (i.e., mean and standard deviation) of the data in each category are calculated and used as initialization values for $B_{i,j}$.

IV. Experiment & Results

The presented method (SSBP) is applied to data collected from a turnout system of the Turkish State Railways located in Babaeski, Tekirdag. The following subsections discuss the data collection, failure progression, and results of the SSBP.

A. Data Collection

The system used for data collection is an electro-mechanical type turnout with two drive rods, one for each rail. Nine sensors were installed in the turnout system: two force sensors for each drive rod, one current, two voltage (separate sensors for forward and backward movement), two proximity sensors for each rail and two linear rulers for each drive rod. The most commonly used sensors in the literature are current and force sensors [24]. Force sensors are electrical sensing devices that are used to measure tension and compression forces. Tension cells are used for measuring a straight-line force "pulling apart" along a single axis; the force is typically denoted as positive. Compression tension cells are used for measurement of a straight-line force "pushing together" along a single axis; the force is typically annotated as negative. Current sensors measure DC current levels. They receive current inputs and provide outputs as analog voltage signals, analog current levels, switches, or audible signals. Voltage sensors are used to measure voltage in electric circuits. Proximity sensors measure the distance between the stock rail and switch rail of railway turnout systems. A linear position measuring sensor is installed on stretchers of the turnout system and measures the linear position of the switch rails. Time series data are acquired from both normal to reverse and reverse to normal movements of a turnout system. Figs. 6 shows the sensors installed in turnout system.

B. Failure Progression Mechanism

There are multiple failure modes in a turnout system. The dry slide chair failure mode is the most frequently occurring failure in turnout systems [22]. Slide chairs are the metal platforms installed on twelve wooden traverses, on which the rail is located, as illustrated in Fig. 7. Slide chairs are oiled periodically and in a fault-free system these slide chairs are oily.

Switch rails move back and forth on the slide chairs on the twelve traverses. They move around 17.5 cm on the slide chair located on the traverse closest to the turnout system. As the traverse gets far away from the turnout system, the movement on that traverse gets smaller. When dry/contaminated slide chair failure modes occur, the friction in the slide chair increases, leading to increased force in the force sensors and changes in voltage and current signals in the motor. In addition, the time to complete the movement may increase.

The failure progression from the fault-free health state to the failure health state is modeled using the exponential degradation mentioned. The natural progression of the failure mode occurs over a long period of time due to weather and environmental effects. Thus, it is not practical to wait and observe the natural progression of the failure mode. In addition, if the failure progresses naturally, the observation of health states becomes very difficult, if not impossible. In this work, the progression of the dry slide chair failure mode is modeled.

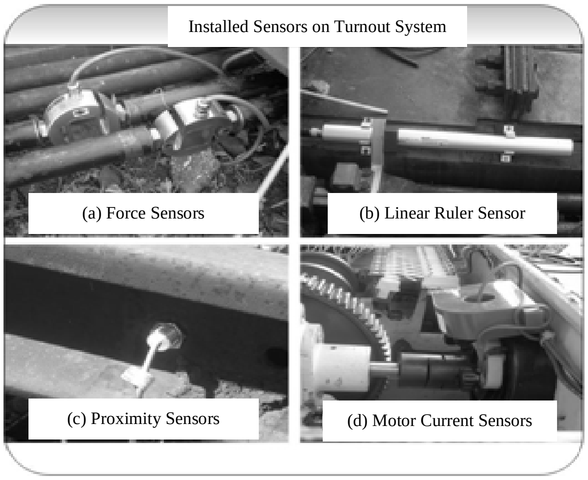


Fig. 6. Sensors used for data collection installed in turnout systems

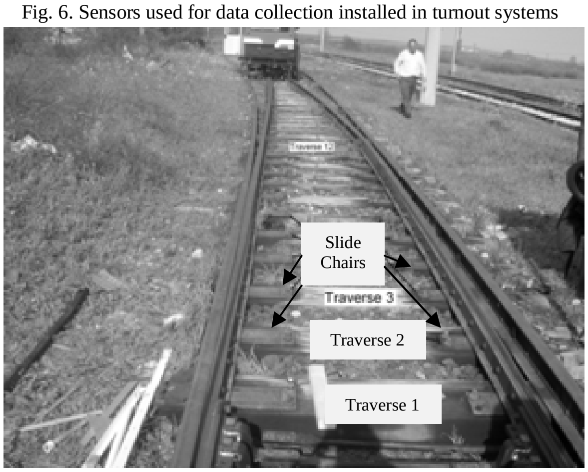


Fig. 7. Modeling the Dry/Contaminated Slide Chair Failure Mode

The failure state is defined as the state when all twelve slide chairs are dry or contaminated. The slide chairs have not been lubricated for a long time to obtain the failure state. The data from the failure state are collected. Then, the slide chairs in the three farthest traverses from the turnout system are oiled, and data are collected. Then, the next farthest traverse is oiled, and data are collected. The oiling and collection of data is repeated one by one from the farthest to the closest slide chairs of the turnout system until all slide chairs are oiled. All of the slide chairs are oily in the final state, which represents the fault-free state. This is achieved in ten steps, each step representing a health state in the failure progression. As a result, many samples from ten health states are obtained. At this point, the life of a turnout system and the time spent in each health state in the failure progression are obtained using exponential degradation modeling with the following parameters: $\phi = 1$, $\mu_\beta = 0.8$, $\sigma_\beta = 0.1$.

An example of current and force signals among ten turnout systems that progress from fault-free to failure states with various lives is shown in Fig 8. As seen from this figure, 13 samples are collected from this turnout system from fault-free to failure state. In other words, its life is 13 units. One can observe the change in the current and force signals as the failure progresses.

This paper uses only the dry slide chair failure mode for the case study and all other conditions, such as operating conditions and wear in the components of the turnout system, are assumed to remain constant. This is a reasonable assumption because all the data are collected in one day, and the dry slide chair failure mode is obtained unnaturally as mentioned above.

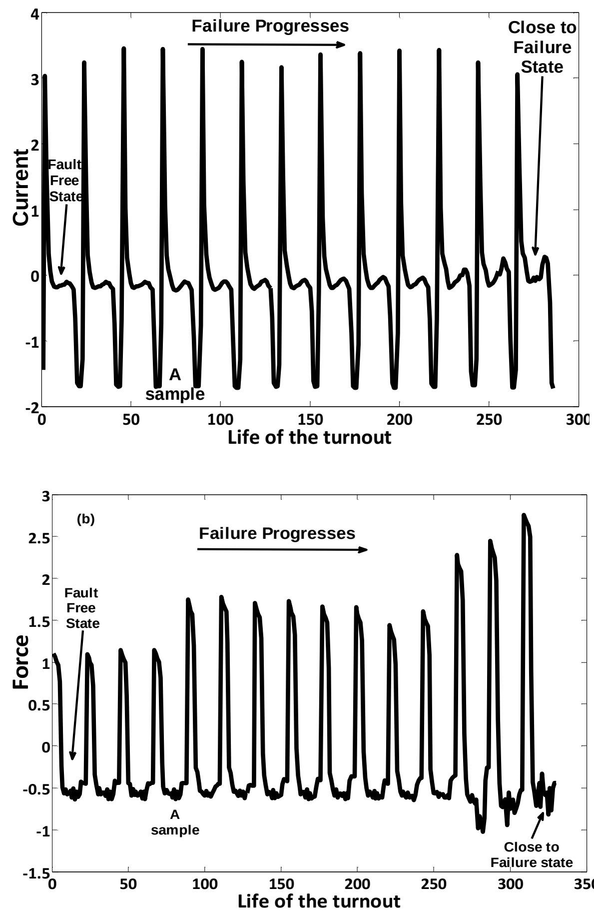


Fig. 8. a) Current b) Force signals with failure progression from ‘fault free’ state to ‘close to failure’state

C. Results

The samples are divided into training and testing groups, with 80% of the samples in the training and the rest in the testing group. The training data are clustered using the number of clusters from two to ten, and the CH cluster validity index is calculated and displayed in Fig. 9. The maximum of the evaluation function (which indicates the best number of clusters found) occurs at eight clusters. Thus, failure progression should be modeled with eight health states. Note that when the failure progression was modeled, ten unnatural health states were used. When analyzing the health state clustering results, it is observed that health states 8, 9, and 10 are combined into one health state. This is logical considering the variance increase in the states close to failure. However, the best health state number found will be checked with forecasting effectiveness to validate the result obtained with the cluster validity index.

Two models (i.e., the SSBP and the HHMM model) are analyzed: samples from the training and testing data are selected, the health states are identified and health state forecasting is performed for both methods. Transition probabilities from both models are extracted, and the expected remaining useful life is calculated as discussed in section III.

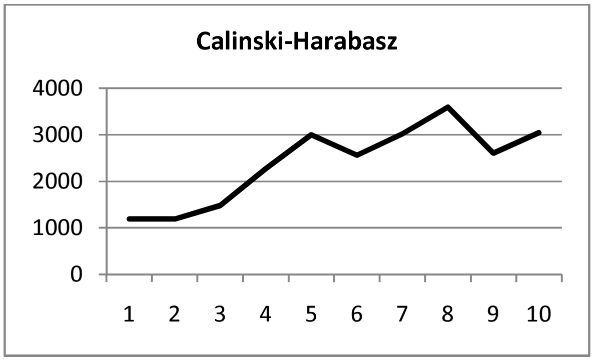


Fig. 9. Evaluation of the number of clusters

The effectiveness of the estimated RUL (RUL_e) is calculated by comparing the RUL_e with the real RUL (RUL_r). The real and estimated RULs calculated using HHMM-based prognostics and the SSBP are displayed for ten turnout systems in Fig. 10. Each graph represents one of the turnout systems. The *x*-axis represents the age of the system, whereas the *y*-axis represents the remaining useful life of the system. The dashed line represents the real RUL of the system given the current age. Note that the sum of the *x*-axis and *y*-axis for the real RUL gives the life of the system. The solid line represents the estimated RUL.

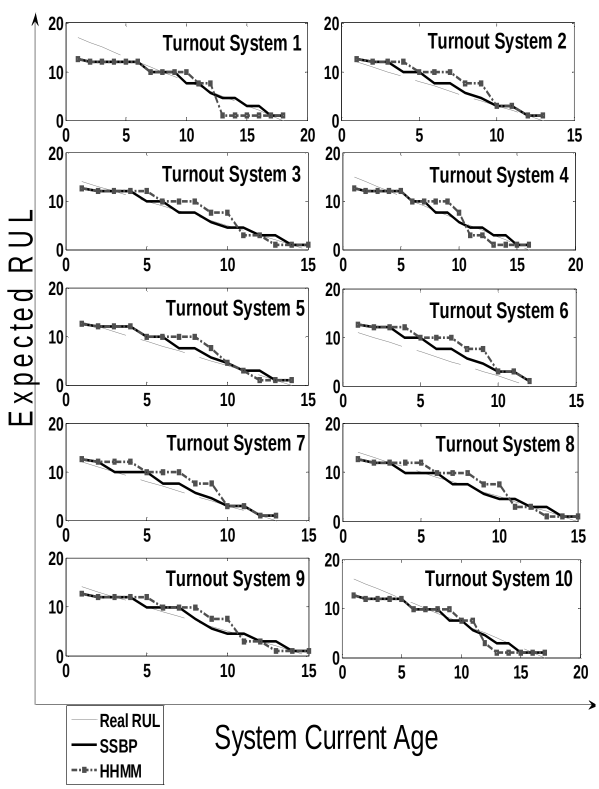
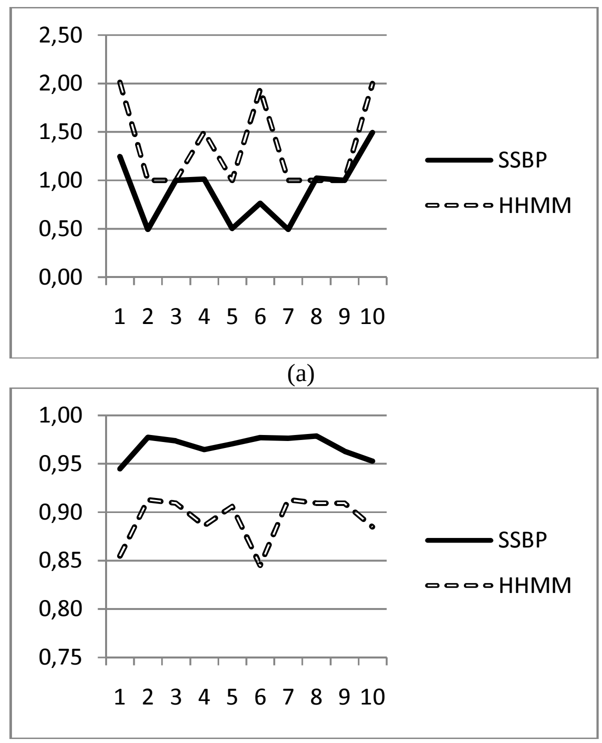


Fig. 10. RUL_r and RUL_e for ten turnout systems with HHMM and SSBP

The root mean square error (RMSE) and r-square values between real RUL (RUL_r) and RUL_e are used as measures to evaluate the effectiveness of the prognostic method in [26] and [30]. Figs. 11 displays the RMSE (Fig 11.a) and r-square (Fig 11.b) between the RUL_r and RUL_e obtained with HHMM and SSBP. The *x*-axis represents the turnout systems, whereas the *y*-axis gives the RMSE and r-square values. It was expected that HHMMs would outperform the presented simple prognostics method, but the opposite was true. The RMSE values are smaller and the r-square values are greater for the presented method. One can conclude that the optimization within HHMM during training makes the parameters worse from a prognostics perspective, considering its design and technical requirements.



(b)

Fig. 11. Comparison of SSBP and HHMM using a) RMSE b) R-square

The presented method is very simple and outperforms HHMM-based prognostics. As a disadvantage, the presented method has restrictions on state transitions that allow transition of a state only to itself and a consecutive state.

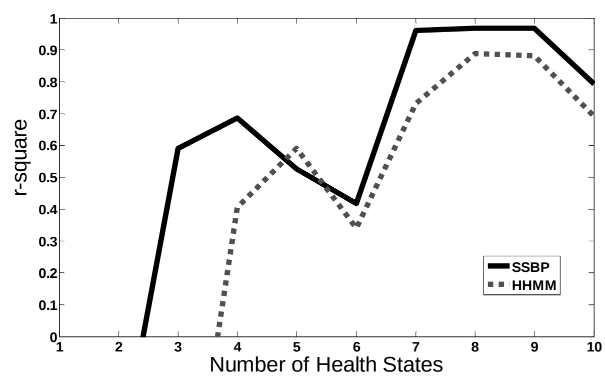


Fig 12. r-square values for different numbers of health states

Fig. 12 displays the r-square values of RUL_r and RUL_e for different health states. The r-square values are negative for the second and third health states and starts increasing thereafter. The highest value obtained is with the eighth and ninth health states, and the r-square value starts decreasing beyond the tenth health state. Note that eight health states were recommended by the CH cluster validity index. Thus, the prognostics results support the result of the CH cluster validity index.

V. Conclusion

Failures often go through several states before making the system unusable. It is critical to identify and forecast these health states as the failure progresses for effective usage of the system. Railway turnouts are one of the most important components of railway infrastructure. Although several studies on failure identification in turnout systems are present in the literature, health state estimation and forecasting have not been reported. One of the most important difficulties in failure progression analysis is the inability to observe the natural progression of failures due to time constraint. Failures occur slowly and obtaining statistically enough failure progression data may take years. This paper presents a strategy to collect data with a given failure degradation model. Then, a simple prognostic method (SSBP) is presented. SSBP and HHMM based prognostic methods are applied to data obtained from a turnout system in the Turkish State Railway and their results are compared. The presented method outperforms the HHMM-based prognostics in the paper. In addition, a validation strategy for health state estimation is presented in the paper.

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