Anticipating Railway Operation Disruption Events Based on the Analysis of Discrete-Event Diagnostic Data

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Public transport reliability is a highly important factor affecting passenger service quality, transportation mode choice, and operating costs. Unreliable service increases operating costs and reduces patronage. In railway systems reliability is significantly influenced by the technical reliability of infrastructure and rolling stock systems. To meet the stringent requirements on reliability and availability, many advanced railway systems and components include monitoring and diagnostic tools. The data generated by these systems can be supplied to data-based methods predicting reliability.

Approaches to predict component failures and remaining useful life are usually based on continuously measured diagnostic signal data. The use of event-based diagnostic data is limited.

This paper describes our research applying Echo-State Networks (ESN) in combination with Restricted Boltzmann Machines (RBM) and fuzzy logic to predict potential railway network disruptions based on discrete-event diagnostic data. The case study focuses on predicting impending failures of a train door system on the level of an individual system potentially causing disruption events of railway operations.

The proposed approach achieved an average prediction accuracy of 97 %. The research results demonstrate the suitability of the proposed combination of methods for use in predicting railway operation disruption events. The findings show that the prediction of medium-term class event patterns is especially helpful since railway operators can use this information to take remedial actions to prevent the disruption.

1. Introduction

In railway systems with high frequency service, small operational disruptions can lead to cascading events throughout the network. Anticipating and preventing technical failures of single components or systems can significantly improve overall service reliability, which is a decisive factor for transportation mode choice. This can be achieved by predicting impending disruption events caused by technical failures of single components or systems.

Both railway infrastructure systems as well as rolling stock systems are increasingly equipped with monitoring and diagnostic systems. These diagnostic systems allow operators to identify failure causes and locations of failures in shorter times and thereby provide higher availability of systems.

Diagnostic systems can be generally subdivided in those that monitor a parameter continuously and enable therefore an inference on the condition of the system, and those that automatically record events. The recorded discrete events can range from confirming an enabled function to indicating that a signal exceeds defined limits. Some of these events are used to warn the train driver or to assist the maintenance crew in their fault finding and corrective actions.

Diagnostic systems usually provide huge amounts of high dimensional and dynamic data that is non-linear and can be difficult to interpret and handle with physical models. Therefore, data-based methods are increasingly applied to extract the information in the data. It is assumed that there is a huge amount of

structure in the data, but the structure is too complicated to be represented by a simple model. In these cases, machine learning techniques are usually applied.

Different machine learning techniques have been applied to different problems of reliability prediction, diagnostics and prognostics, such as several types of neural networks (Zio et al., 2012), support vector machines (Pai, 2006) and combinations of different techniques (Caesarendra et al., 2011).

For continuously measured signals there are several studies with the application focus on railway systems (Roberts and Silmon, 2012). Many of the studies focus on railway infrastructure systems (Garcia Marquez and Schmid, 2007). Two of the studies focussed specifically on train door systems (Lehrasab et al., 2002) and (Smith et al., 2010), as the present study. In both studies, continuously measured diagnostic data were used as indicators allowing inference on the performance of the considered systems. Examples of such indicators are electrical current and voltage signals from the open/close cycles, closing and opening times, pressure, velocity and airflow. In (Smith et al., 2010), the input parameters were used in a regression model to derive the level of performance of the system. In (Lehrasab et al., 2002) a combination of different methods was applied to classify performance indicators and to indicate faults. The achieved classification accuracy was between 66 % and 90 %. The network types applied in these studies were Multilayer Perceptrons (MLP) with different network design principles (such as e.g. cascade correlation), Radial Basis Functions (RBF) and Self-Organizing-Maps (SOM).

Discrete-event diagnostic data contain less information on the condition of the system and the evolution of the condition in time, compared to continuously measured diagnostic data. There are therefore many differences compared to using continuously measured signals. A previous study (Fink et al., 2013) has shown that discrete-event diagnostic data can be used for predictions with good classification precision. In the present study a different approach is applied: the data is pre-processed in a different way and the classification is now distinguishing between short-term, mid-term and long-term occurring events, compared to only two classes used in the previous study. Furthermore, the applied algorithms are partly different. The approach proposed in the present study applies Restricted Boltzmann Machines (RBM), Echo State Networks (ESN) and fuzzy classification for predicting potential operational disruption events.

Discrete-event diagnostic data from the railway door system was considered in this study. Door systems can directly or indirectly lead to delays in railway operations. For example, if a sliding step, part of the primary door system designed to bridge the gap between the train door and the platform, cannot be retracted, the train will not be permitted to depart. In this case the sliding step must be retracted manually, either by the conductor or the driver, which results in a delay. Therefore, anticipating failures of door systems can prevent operational disruptions and service delays and thereby lead to improved reliability and efficiency. The prediction of mid-term occurring events is particularly beneficial for anticipation and prevention.

The remainder of the paper is organized as follows. The next Section describes the theoretical background of the applied methods, which include fuzzy logic, Restricted Boltzmann Machines (RBM), Echo State Networks (ESN). The full algorithm applied to predict impending diagnostic events with the potential for causing railway operational disruptions is introduced in Section 3. Section 4 presents the results obtained applying the algorithm to the passenger train door system diagnostic data. Finally, Section 5 discusses results and makes recommendations for further research.

2. Theoretical background

In this Section, the theoretical background of the applied algorithms is summarized, namely Fuzzy logic, Restricted Boltzmann Machines and Echo State Networks.

2.1 Fuzzy logic

Fuzzy logic is the logic of fuzzy sets, which enables dealing with real world phenomena and especially with vagueness. Fuzzy logic enables the transformation of linguistic variables into appropriate set theory (Zadeh, 1973). It allows partial set memberships, contrary to crisp set memberships originating from binary logic in which a value is either part of the set or not. The degree of membership of a fuzzy logic variable is between 0 and 1 and is defined by a membership function. A membership function can have different forms, such as triangular, trapezoidal, Gaussian.

In classification, patterns are classified as belonging to a specific set based on similarity in the data. Especially if the classes can be described by linguistic variables the application of the fuzzy logic is beneficial.

In the current case study, three classes are defined: data patterns leading to a disruption event in the short-term, in the medium-term or in the long-term. This classification is sufficiently precise for the operators to anticipate the failures. The medium-term class event patterns are especially helpful since railway operators can use this information to take remedial actions to prevent the disruption.

2.2 Restricted Boltzmann Machines (RBM)

Restricted Boltzmann Machines are networks of symmetrically connected neuron-like units. RBMs are also referred to as stochastic neural networks. Boltzmann machines consist of two layers: a visible layer and a hidden layer. Each unit in the visible layer is connected to all units in the hidden layer and vice versa. The visible layer contains the input parameters; the hidden layer contains the latent parameters that the networks learn (Ackley et al., 1985). The hidden layer learns to model the distribution of the visible layer of variables. However, the units within one layer are not interconnected. Therefore, the networks are called "restricted". This restriction simplifies the learning process.

The learning process of RBMs can be either supervised or unsupervised. Single RBMs can be composed to more complex structures, such as in deep learning, in this case their weights are adjusted after an initial unsupervised learning process by back propagation learning algorithm (Hinton et al., 2006).

2.3 Echo State Networks (ESN)

Echo state networks are a specific type of recurrent neural networks. Similar to other recurrent neural networks, ESN are able to exhibit dynamic temporal behavior and have a memory (Jaeger, 2005). ESN are typically applied for modeling complex dynamic systems. They have been applied for many practical applications, such as iterated prediction of time series, signal classification and dynamic pattern recognition tasks (Verstraeten, 2009).

The main structural element of ESN is a reservoir rather than a layered structure. The ESN are defined by randomly and sparsely connected neurons, which are organized in the reservoir. The weights between the connected neurons within the reservoir are fixed and are not trained during the training process (Jaeger, 2005).

In the training process, input signals ("training signals") are presented to the reservoir to induce nonlinear responses. The single neurons exhibit an "echoed" response to the training signal and generate a variation or a transformation of the induced training signal. Subsequently, a desired output signal is determined by a trainable linear combination of all the generated response signals. In supervised learning a teacher signal is fed back to the reservoir. The process is illustrated schematically in Figure 1.
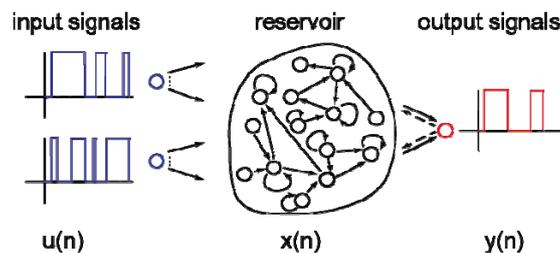

Figure 1 Functional Principle of Echo State Networks, Based on (Jaeger, 2005)

The ESN's main difference from other neural networks is that only the weights of the reservoir output signals are trained (Jaeger, 2005). The weights of the connections within the reservoir are not trained but are generated randomly. This approach significantly reduces the learning process compared to other algorithms (e.g. back propagation through time). One of the major properties of the echo state network is the so-called echo state property. This property ensures that the network has a fading memory and thus that the influence of initial conditions, which are randomly generated, diminishes asymptotically (Verstraeten, 2009). Therefore, at the end of the training process only learned relationships influence the output.

3. Applied data and algorithms

3.1 Applied data

In this study diagnostic discrete-event data from a railway fleet consisting of 52 train sets, part of which consists of 9 cars and the other part of 11 coaches, each with two doors on each side, was applied. The available observation period was 313 days (approximately ten months). It is assumed that due to the size of the fleet, the data set covers all relevant combinations of different parameters and that these differences are reflected in the occurrence of the diagnostic events. The data are considered sufficient to demonstrate the feasibility of the approach.

Data were collected automatically by event recorders. These begin recording parameters when a predefined diagnostic event occurs. The number and character of parameters recorded depends on the affected system. The parameters include speed, outside temperature, overhead line voltage etc. The

recorded events are always assigned a time stamp, train location (i.e. train number, car number) and actual location via GPS. Additionally, the usage profiles of each door can be deduced from the diagnostic data. Diagnostic events fall into one category:

- Driver action required – high priority;
- Driver action required – low priority;
- Driver information;
- Maintenance.

Depending on the category, the corresponding events will be communicated to the driver or only to the maintenance crew. High priority diagnostic events are those that can potentially result in a delay-causing event. For door systems, high priority events that require driver action include those of the sliding steps that cannot be retracted or of the doors that do not close prior to departure. The signals that are relevant for maintenance include information on deviations from the normal operation of various door system components and subsystems.

There are 261 distinct event codes for the door system considered in this research. These event codes indicate the specific door affected by the event. For instance, there can be four different codes for one type of event (one for each door in the car). In this research, the allocation of an event to a specific door system is performed in the structure of the data and not in the coding of the events. Therefore it was possible to reduce the 261 codes to 72 distinct events. Out of the 72 events, 12 required a high priority driver action.

Note that the functionality of door systems can also be affected by external influences, such as passengers obstructing the door. But, only those events originating from technical malfunctions can be predicted by functional data-driven algorithms.

For this study one of the high priority events with a root cause in technical faults is selected to demonstrate the feasibility of the approach.

3.2 Preprocessing of input data

In this research, the observation time window was set at four weeks because this was considered sufficiently long for different diagnostic event patterns to evolve and given the amount of available data (ten months). In order to cover many different combinations of diagnostic event patterns and also to generate a sufficient number of input signals, the data patterns were generated by moving a four-week fixed time window over the 313-day study period, one day at a time. The consequence of this approach is that the time periods overlap and the data patterns can show similarities.

It is assumed that the last occurred signal that represents an event has the biggest influence on the system. Therefore, the time since the last occurred event is calculated for all the signals. Thereby, the whole history of the data range is used and not only the signals occurring in the defined observation window.

Before presenting the data to the algorithm the inputs were preprocessed. The inputs were normalized to be in the value range between 0.1 and 0.9. In order to capture possible deviations from the minimum and the maximum values which are not covered by the selected data set and to ensure a better generalization ability, the data range was extended symmetrically by 20 %.

In order to ensure a good learning capability of the algorithm, the input data set is balanced in such a way that the data set is composed of equal numbers of patterns from each of the three classes. This approach is valid only if the selected data patterns from one class are representative of the class.

Subsequently, the data sequence is randomized in order to ensure that the generalization ability of the algorithm is not affected by the sequence of the presented patterns.

For this case study, trapezoidal membership functions were selected. The short-term events occur within less than 11 days, the medium-term events occur within the time period of 7 and 37 days, and the long-term events occur within longer than 30 days (Figure 2).
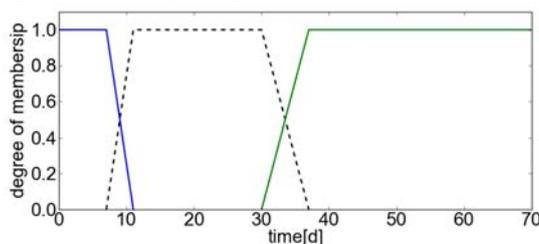

Figure 2 Trapezoidal membership functions (short-term, mid-term, long-term)

3.3 Applied algorithm

The applied algorithm was composed of a Restricted Boltzmann Machine and several Echo State Networks, applied to subsets of the data either in parallel or in series. The proposed algorithm learns to distinguish between the patterns assigned to the three fuzzy classes.

In the first step, the input is presented to a RBM which learns in an unsupervised manner the probability distribution of the hidden layer. The output of the RBM, the probability distribution of the hidden layer, is evenly partitioned onto three subsets with overlapping of the boundaries by 10 % of the input length for each of the subsets. Each of the subsets is presented to an echo state reservoir with different reservoir parameters. The outputs of the three reservoirs are joined in the next step in a single reservoir which is trained in a supervised manner with ridge regression. Ridge regression is similar to ordinary linear regression, but with the difference that a regularization term is included in the minimization problem of residuals, which imposes rigidity (Hoerl and Kennard, 1970).

In order to compare the results, the class with maximum degree of membership in the original data set is compared to the predicted class.

4. Results

The holdout technique is used to evaluate the generalization ability of the algorithm classification. For this purpose, the data set is divided into two subsets, in a way that both are representative of the underlying distribution of the entire data set and are independent. The algorithm learns based on the first subset of training data to generalize the data patterns. The second subset of testing data is used to test the generalization ability of the algorithm. In this research 90 % of data were used for training and 10 % for testing. Totally, 1075 data patterns were presented to the algorithm during the training phase. The algorithm was tested on 119 patterns. As mentioned above, the composition of the primary data set (including training and testing data sets) is balanced between all of the three classes. Both subsets, for training and testing, are also balanced by randomizing the sequence of the patterns.

In the first step the misclassification rate is computed to evaluate the overall performance of the algorithm. The misclassification rate does not distinguish between the classification performances of the algorithm for different classes. It only gives information on the rate of patterns that were misclassified by the algorithm, irrespective of which of the three classes was misclassified. In the present study the misclassification rate was 3.5 %.

The confusion matrix is a performance assessment parameter that can distinguish between the classes and compare the classification performance within a single class (Aronoff, 1982). The classification performance within each of the classes is displayed in Table 1. The Table shows that the classification performances of the classes "short" and "long" give a similarly good performance of correctly classified patterns, above 97 %. The classification performance for the class "mid" is 95 %, slightly below that of the other two classes. This is due to more similarity of data patterns of the "mid" class to those of the other classes.

Table 1: Confusion matrix for the classification results

	Class "short" (predicted)	Class "mid" (predicted)	Class "long" (predicted)
Class "short" (actual)	97.4 %	0 %	2.6 %
Class "mid" (actual)	2.3 %	95.3 %	2.3 %
Class "long" (actual)	0 %	2.7 %	97.3 %

5. Conclusions and discussion

The study proposes a combination of algorithms to extract information on the condition of a railway system from diagnostic event data. The proposition applied to a specific case study of a door system leads to good results in terms of precision of classification of potentially occurring disruptions in railways operation.

The main practical purpose of the performed predictions is to reduce the number of operational disruption events and thereby increase service reliability. This approach enables railway operators to reduce corrective maintenance actions by improving their planned predictive maintenance actions and thus to reduce overall maintenance costs.

The prediction of operational disruptions on mid-term horizon is the most beneficial for railway operators. In principle, if all the mid-term events could be anticipated before occurrence, there would be no short-term events. Actually, those events in which the fault progression is accelerated and the patterns cannot be detected in mid-range will still occur even if the anticipation of predicted mid-range failures is successful.

Despite the good performance witnessed in the case studied, there remain some limitations. First, only diagnostic event data could be included in the model developed. The significance of the results could be increased by integrating additional data in the approach (e.g. data on performed maintenance activities).

There are several other ways to extend the research. The history of the data is partly included in the approach by computing the interval from the present point of time to the last occurred event. Integrating the evolution of the condition in time would enable dynamic monitoring of the process: an observed "jump" from class "long-term" to class "mid-term" would initiate a more attentive monitoring procedure and alert maintenance planning.

Additionally, part of the data could not be used because the record of the events does not only contain disruptions caused by technical malfunction but also those caused by external influences, such as passengers obstructing the door etc. To be able to distinguish the high priority events due to technical root causes, it might be beneficial to introduce filtering algorithms that can filter the data in an unsupervised manner in order only to distinguish those data patterns with the technical root cause.

6. Acknowledgement

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