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Development of a condition-based deterioration model for bridges in Rhode Island

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DEVELOPMENT OF A CONDITION-BASED DETERIORATION MODEL FOR BRIDGES IN RHODE ISLAND

BY

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ABSTRACT

Almost one in four bridges in Rhode Island have been rated as structurally deficient in 2017 according to the American Society of Civil Engineer‘s (ASCE) most recent Report Card. This makes Rhode Island the state with the highest rate of structurally deficient bridges in the USA. Since the allocated financial resources from federal, state and local level are scarce, effective bridge management is of crucial importance to maintain bridges in a sufficient condition and preserve them from decay. A major part of Bridge Management Systems (BMS) is prediction models, which have become increasingly important in their function to forecast bridge durability and their need for repair and maintenance.

In this study, three deterioration models, one for each major bridge element (i.e., deck, superstructure, and substructure) have been developed for the state of Rhode Island. The deterioration models were designed as Dynamic Bayesian Networks (DBN), which are based on annually recorded inspection data of Rhode Island’s bridges provided by the National Bridge Inventory (NBI). Several predictions have been made with varying input parameters for the model‘s variables, which illustrate the capability of the developed prediction models. Moreover, the DBN's updating ability is demonstrated by several sample predictions which incorporate the influence of simulated maintenance actions.

Additionally, the NBI database has been used to investigate the correlation between several bridge related parameters and the deterioration of Rhode Island’s bridges.

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1. INTRODUCTION

1.1 Motivation

Infrastructure facilities are an indispensable element for every society. Their function in moving people and connecting communities and business is an essential cornerstone for economic growth. Within this infrastructure, bridges play a central role. The assurance of its functional capability is of crucial importance for a safe traffic flow. The American Society of Civil Engineers (ASCE) is providing a way to determine what the quality of America‘s infrastructure is, by creating an assessment of all essential infrastructure facilities in the USA. This assessment is conducted every four years and the results are published in the ASCE's Report Card for America‘s Infrastructure. With grades from A to F, a rating shall give a rough estimate of the infrastructure's condition. In the most recent Report Card of 2017, America‘s infrastructure has been rated with a D+. The rating is put together of 16 different categories in total. One of those categories is America‘s bridges, which have been graded slightly better with a C+. However, both results are by no means satisfactory. Taking a closer look at the report, there are currently 614.387 bridges in the USA, 9.1% of which have been declared as structurally deficient. Although the condition of the nation‘s bridges has improved over the last 10 years, as in 2006 about 12% of all bridges were rated structurally deficient, the individual states show widely differing values. While Utah has with 1.6% the lowest amount of deficient bridges on average, Rhode Island stands out with alarming 24.9%. Moreover, the service life of many bridges in the USA is about to come to an end. Almost 40% of all bridges in the USA have already reached their 50^{th} year or even more. Since most bridges have been designed for a service life of 50 years, major repair and rebuilding measures or the closing of the affected bridges will be an inevitable consequence.

The maintenance and repair of America's bridges require a lot of investment. For instance, in 2012 approximately $17.5 billion dollars were been spent on the repair and maintenance of bridges, according to the federal government. However, the provided financial resources are nowhere near sufficient. Currently, there is an estimated backlog of about $123 billion dollars for bridge rehabilitation [1]. But not only are more financial resources necessary from federal, state and the local level, also engineers, planners, and transportation agencies have to ask themselves what can be done to deal with this problem. An effective tool to manage and optimize the process of inspection, maintenance and the repair of bridges, and therefore save immense financial resources, are Bridge Management Systems (BMS) [2]. An essential component of a BMS is deterioration models, which are able to predict the disrepair of bridges, and can further be used to schedule and manage inspections and maintenance actions. Furthermore, the deterioration models can be used to examine the impact of certain parameters, like material properties, the bridge's environment, and daily traffic on the deterioration of bridges. In summary, bridge deterioration models contain great potential to improve decision-making processes regarding bridge maintenance.

1.2 Objective and Scope

Within this study, one objective was to investigate possible correlations between the deterioration of bridges in Rhode Island and several bridge related factors. However, the main goal of this study was to develop a deterioration model for bridges in Rhode Island. In fact, three deterioration models were developed for the individual bridge elements namely deck, superstructure and substructure. The purpose of these deterioration models is to predict the future condition of the respective bridge elements.

The proposed deterioration models were designed as Dynamic Bayesian Networks (DBN), which describes the relationship between several factors that affect bridge deterioration and the individual bridge element conditions. In order to specify the DBNs, a comprehensive source of data was required. For this purpose, the National Bridge Inventory (NBI) was chosen, as it records detailed bridge information for almost every bridge in the USA since 1992. From the NBI several items were selected to represent variables in the deterioration models. Before the deterioration models could be developed the obtained datasets from the NBI needed to be filtered in order to sort out unusable and incorrect data. Furthermore, using sensitivity analysis, the impact of the model's variables and the bridge elements conditions were investigated.

1.3 Outline

This thesis will describe in detail how the proposed bridge deterioration models for each bridge element (i.e. Deck, superstructure, and substructure) were developed using Bayesian theory and the NBI database. Beforehand, the obtained data from the NBI was analyzed to examine the relevance of several selected parameters regarding bridge deterioration in Rhode Island.

Chapter 2 two provides a literature review on bridge management, including an introduction to Bridge Management Systems (BMS), the NBI and the bridge element condition ratings provide by the Federal Highway Administration (FHWA), which are the basis of the developed deterioration model. This chapter further gives background information on deterioration of reinforced concrete bridges and preventative design and maintenance. In Chapter 3, the theory of Bayesian Networks (BN) and Dynamic Bayesian Networks (DBN) is described. Furthermore, a description of two methods on how to determine BN parameters is given. Chapter 4 includes a parameter analysis using the NBI database. In this chapter, the obtained NBI datasets were filtered before deterioration rates were computed in order to analyze any correlation between the individual bridge elements and several selected NBI items. In Chapter 5 the development of the deterioration models is described in detail, using the methods explained in Chapter 3. The ability of the developed models is demonstrated by the performance of several predictions based on various assumptions. Furthermore, this chapter includes the performance of sensitivity analyses to investigate the impact of the model’s variables on the bridge elements. Lastly, Chapter 6 provides the conclusion of this study, consisting of a summary of the performed analysis and gained findings, a discussion of the results derived from the deterioration models output, and finally a recommendation for future work.

2. LITERATURE REVIEW

2.1 Bridge Management

The management and maintenance of infrastructure facilities are of major importance to ensure a functional infrastructure network to the public. With the ever-increasing expansion of America's roads and bridges, the task of keeping the infrastructure in a sufficient condition becomes a challenge which is difficult to execute.

The expenses of maintaining a bridge in good condition, are increasing as bridges become older. Therefore, the controlling of maintenance and repair costs is an important element of bridge life-cycle cost analysis. For local and state transportation agencies, which have large bridge networks under their jurisdiction, and have to deal with limited available funds, bridge management decision making is a complicated and difficult process. To facilitate bridge management, the technological progress of recent years made it possible to develop analytical tools for decision making. These tools, in form of BMS software packages, are increasingly being used by agencies to achieve a well-developed bridge network management.

According to the U.S. Department of Transportation (USDOT), the development of bridge management methods is an important factor for several reasons [3]. First of all, along with the expansion of infrastructure, bridges also tend to deteriorate faster, due to an increase in usage. The ability to perform effective bridge management should be given even for bridge agencies who have to deal with personnel constraints. One of the greatest issues and most significant factors regarding the goal of keeping bridges in satisfactory condition are limited financial resources [3]. Since bridge agencies have to take care of a great number of bridges, it is inevitable to apply strategic management practices, in order to maintain the whole bridge network in an acceptable condition and keep life cycle costs as low as possible. To effectively perform these tasks computerized bridge management tools are used by bridge agencies [4].

2.1.1 National Bridge Inventory (NBI)

The National Bridge Inventory (NBI) was initiated in 1972 with the purpose of providing a database, which stores detailed information for almost every single bridge in the United States. It contains over 100 items for each bridge, which constitute relevant bridge information such as location, owner, year built, average daily traffic, design load, type of service, structure length, inspection date, and many more. These items are listed and defined in the *Recording and Coding Guide for the Structure Inventory and Appraisal of the Nation's Bridges*, provided by the Federal Highway Administration (FHWA). The main purpose of this guide is to give state, federal and other agencies guidance on how to evaluate and code specific bridge data, by providing explicit explanations and instructions for coding data that will prepare the items in the NBI [5].

The items in the NBI for each bridge, can basically be divided into two groups, such as which do not change over time, usually data regarding the construction of the bridge such as year built, location, type of service, and data which needs to be updated in certain periods, such as average daily traffic and condition ratings.

The appraisal data in the NBI has to meet the requirements of the National Bridge Inspection Standards (NBIS). In the NBIS, the federal requirements for inspection operations, the demanded number of inspections, necessary qualification of the inspectors, as well as the establishment and administration of a state bridge inventory are specified. According to the NBIS, each highway state department is required to provide the capability to conduct inspections, generate reports, and give ratings, pursuant to the American Association of State Highway and Transportation Officials (AASHTO) manual. The Transportation agencies and bridge owners have to keep a record of bridges which include fracture critical members. In the course of this, it is necessary to specify their location, give a description of the respective bridge members and keep a record of past inspections along with the applied procedures, which were made on the affected members. A fracture critical member, as defined in the NBIS, is bridge member under tensile stress, whose malfunction will result in a collapse of the entire bridge or certain bridge parts [5].

It is the responsibility of each state to generate and hold a bridge inventory, including the collection and storage of the required data. The time limit to register a newly completed bridge in the inspection reports and computer inventory files is 90 days for bridges under the responsibility of the state, and 180 days for all other bridges on public roads within the state. The same is applicable in cases of alteration or reconstruction of existing bridges, as well as the placement of load restriction signs in front of the affected bridges.

The NBIS further requires state and local agencies to conduct bridge inspections every 24 months. Exceptions can be made for short-span bridges in good condition with low average daily traffic. In this case, an inspection period of 48 months is sufficient. However, for bridges that show critical damage and deterioration, it is recommendable for bridge owners to inspect the affected bridges at intervals of less than 24 months [6]. In general, the interval of bridge inspections depends mainly on certain bridge characteristics such as age, traffic values, current condition and examined defects. The analysis of these characteristics is the task of the person who is responsible for the inspection program. For some bridges, though, the inspection interval is allowed to extend 48 months. These bridges need to have proved satisfactory values for the above-mentioned characteristics in most previous inspections [5].

To guide state, federal and other agencies in inspecting bridges and creating reports, the AASHTO provides a manual to evaluate the condition of bridges (AASHTO Manual for Condition Evaluation of Bridges). Along with the Bridge Inspector's Training Manual/90, the inspectors receive explanations of how to create detailed reports about the condition of the bridges major components. The values of several items in the NBI are based on these reports, especially the condition ratings for deck, superstructure, and substructure. According to the *Recording and Coding Guide for the Structure Inventory and Appraisal of the Nation's Bridges*, inspection reports should, in general, be composed of three major components [5]. First of all, a statement of what measurements had been taken in the course of the inspection. Further, the description of discovered damage or deterioration, as well as an evaluation of the affected bridge components. And finally, a definition of all critical members, which should be kept under close surveillance in following inspections, along with comments on instructions, concerns or recommendations. An inspection report should further include drawings, test results or calculations, if applicable [5].

A bridge inspector is required to have a certain minimum qualification. This qualification can either be a registered professional engineer, or holding the qualification for such registration, or to have at least ten years of experience in inspecting bridges, along with the completion of a broad training in accordance with the Bridge Inspector's Training Manual. To be in charge of a bridge inspection team, a more comprehensive qualification is required, which is stated in the NBIS [5].

The NBI database can be used to identify which bridges have a strong need in maintenance, repair and replacement actions. Because of this, the NBI is the basis for several BMS, such as the Indiana Bridge Management Systems and Pontis Management System. Several items of the NBI are required for analysis in those BMS. In general, the performance and efficiency of a BMS depend mainly on the speed and storage capabilities of its database.

2.1.2 Bridge Condition Ratings

To determine and evaluate the condition of bridges, periodic inspections are an essential instrument [7]. For highway bridges, the whole bridge, as well as major elements, should be examined independently every two years. These elements include the bridges deck, superstructure, and substructure [8].

Based on these inspections, condition ratings of the whole bridge and the individual elements will be developed subsequently. These condition ratings are developed by the FHWA for all bridges in the USA and stored in the NBI. The purpose of the condition ratings is to give a rough estimation of the overall structural condition of the respective bridge components, by comparing their current condition to the condition right after the construction, which normally shouldn't show any considerable deficiencies [5]. In the course of this, the bridge components should always be viewed as a whole, hence the description of isolated damage and evidence of deterioration should not be considered [5]. The condition ratings are the foundation on which future inspections and maintenance measures are planned [7]. In the NBI, all possible bridge conditions are divided into ten categories, which are labeled with numbers from 0 to 9, where 0 defines the worst condition rating and 9 the best [5].

CONDITION RATING	DENOTATION
N	Not applicable
9	Excellent condition
8	Very good condition
7	Good condition
6	Satisfactory condition
5	Fair condition
4	Poor condition
3	Serious condition
2	Critical condition
1	'Imminent' failure condition
0	Failed condition

Table 1: Bridge condition ratings according to the FHWA *[5]*

In Table 1 the condition ratings for bridge elements according to the FHWA are given respectively [5]. A rating of N (not applicable) is given for all structures without decks such as culverts.

The ratings are not subject to equations but are incumbent to the assessment of the responsible inspector [9]. A decisive factor for the accuracy when classifying bridges is, therefore, the professional expertise of the inspector. To remedy this uncertainty, an extensive training of the inspectors is of great importance [10]. In terms of the disrepair of bridges, a great number of factors are playing a role. The primary accountable factors are daily traffic, environmental aspects, and insufficient maintenance actions [8].

By comparing the data from the last years and evaluating their development, prediction models can be created, which are capable of forecasting the future deterioration of the respective bridge. With the aid of these prediction models, prospective inspections and maintenance measures will be planned. As soon as new data is present, it can easily be incorporated to update the deterioration model. These models can also be used to examine the influence of certain parameters on the level of deterioration, like climatic conditions, the age of the bridge or volume of traffic [11].

2.1.3 Bridge Management Systems (BMS)

For the past twenty years, BMS have been the subject of several research projects. BMS are in particular used by transportation agencies for planning bridge maintenance activities and estimating life-cycle costs. The ability of BMS to statistically calculate future bridge condition ratings, and therefore forecast bridge deterioration, paves the way for effective scheduling and budgeting upcoming maintenance actions [4].

The need for bridge management was first realized after the collapse of the Silver Bridge in 1968, due to the omission of timely and proper maintenance and repair measurements. After that, bridge agencies started to approach bridge maintenance in a more systematic manner. Correspondingly, the FHWA introduced the national inspection program to gather bridge data through inspections to further form the NBI, which eventually became the database for most BMS in the USA [4].

The idea of a BMS is to develop an effective strategy to optimize the decision-making process for maintenance actions, given the available financial resources. The goal is to achieve a life-cycle cost as low as possible, while keeping the bridge in a satisfactory level of safety, to assure its serviceability for daily traffic and minimize its risk of failure throughout its lifetime [12]. To develop an effective strategy to reach this goal, all potential risk factors should be taken into account. Bridge management is a planning process, which merges procedures from several disciplines such as structural engineering, business practices, information technology and economic research. BMS come in the form of a computerized tool to help engineers in executing their daily bridge management tasks [4].

A disadvantage of BMS, which constitutes a problem for bridge agencies, despite many years of research and development, is the great amount of required bridge data, which leads to a very time-consuming implementation process [4]. Bridge data usually consists of general bridge information, information regarding designing and construction, inspection and maintenance records, financial records and various other data [10]. An extensive and consistent bridge database is the key element for an efficient and accurate BMS. Therefore, the collection and storage of this information in a database should be attached great importance. At present time bridge information is hardly be recorded manually, since storing bridge data electronically does bring a lot of advantages, as stated by the FHWA in [13]. Electronically stored bridge data can be shared much easier among users and can be retrieved and updated much faster.

The AASHTO provides guidelines for the establishment and usage of BMS. According to these guidelines, a BMS should contain five essential elements: data storage, cost models, deterioration models, optimization and analysis models, and updating functions [14] [10] [12]. As mentioned above, the most important component of a BMS is the database. It contains information that relates to the bridge itself, such as structural data, year built, number of lanes, as well as time-dependent data that needs to be updated by periodic inspections such as, the condition of major elements, traffic volume, and environmental factors. The conditions of the bridges major elements are further used in the BMS to calculate the probability of the future condition and hence the deterioration of the bridge by applying a stochastic prediction model. In most BMS this prediction model is based on the condition ratings in the NBI. Most commercial BMS also include a cost module, to calculate the costs to satisfy the required maintenance and repair measurements (MR&R) to improve the condition rating. In the optimization module, the results of both the cost and the deterioration module are applied, to effectively determine the optimal operation for the bridge network. In order to so, there are generally two methods. In the bottom-up method, which is used in most BMS software packages, the required maintenance activities for every single bridge is determined to eventually improve the whole bridge network, whereas in the top-down method the objectives of the bridge network are defined and in a second step individual bridges are selected [4].

Godart and Vassie gave a broad overview over a number of BMS features, which include the provision of a bridge inventory, prediction of future conditions of major bridge components, along with the bridges prospective load-carrying capacity, determination of deterioration rates and the selection and evaluation of several maintenance and repair options with regard to economic efficiency [15]. It can further include the analysis of the effects of insufficient maintenance actions on safety and traffic congestion and provide its user with an optimal inspection and rehabilitation plan [4].

In some cases of BMS, the output of various sections are required as the input data for other modules. A sufficient database is therefore inevitable to provide a well operating BMS. For instance, the outputs of the condition rating prediction are required as inputs to produce an optimal maintenance program and several other BMS features. Hence the future condition ratings, are indispensable for all related modules to operate properly.

Most BMS are based on the inspection of major bridge components to store data for bridge condition ratings. According to Das, building upon bridge inspections leads to various limitations, since the data obtained through visual inspection is the only source for bridge data, hence bridge elements which might not be visible during inspections are not included in the bridge management process. Therefore, the accuracy of the predicted needs of bridges might not be reliable enough [16].

In many countries, research on bridge management systems has been conducted during the last two decades in order to improve its effectiveness. The most commonly implemented BMS software are Pontis and BRIDGIT, both designed by the AASHTO. These software packages are not just used in the USA, but by bridge agencies all over the world to effectively perform bridge management [4].

Pontis was the first commercial BMS software developed by the FHWA in 1991 and was licensed in 2008 by the AASHTO to over more than 45 state departments of transportations, as well as other organizations in the USA and around the globe. With its establishment, bridge management was brought to a new level in America and several other countries. Since then, the Pontis software package has been continuously updated, introducing new features. It includes all key elements of bridge management and uses condition ratings to predict future condition. The deterioration model which is implemented in Pontis, is based on Markov processes, to calculate the deterioration rates of bridges. As soon as new data becomes available and is updated in the Pontis database, the deterioration module automatically calculates a new prediction of the bridges future condition, without starting it manually. The Usage of Pontis brings various advantages. Pontis compares and balances bridge condition with long-term maintenance expenses to assess and determine an optimal level of investment. Bridge data is effectively stored and organized by applying advanced data management functions. Pontis gives bridge agencies the possibility to customize the bridge management system to the individual needs and demands. It allows its user to modify internal functions and data, in order to adjust them to any particular requirements. In order for Pontis to fully operate, a minimum of input data is required by its user, which is a problem that not seldom prevents bridge agencies from being able to use Pontis. About half of the data that is provided by agencies using Pontis in order to run the system, was gathered through inspections. Periodic inspections are therefore the primary and most important resource of bridge agencies in order to conduct bridge management [4].

Another common used BMS is BRIDGIT, which like Pontis uses bridge condition ratings for health prediction modeling [12]. It was developed by the National Cooperative Highway Research Program (NCHRP) and shows common grounds to Pontis in most essential aspects [10]. Although Pontis and BRIDGIT are the most widely used BMS in the USA, a lot of states have developed their own BMS over the years, such as the Alabama DOT or the Indiana DOT [4].

Apart from the fact that BMS are an effective method to perform bridge management, the user should never carelessly rely on the outcomes of these systems itself, but see them solely as a support tool for decision making.

2.2 Deterioration of Reinforced Concrete Bridges

In the course of time, bridges have become an increasingly important aspect for every society to obtain a well-working infrastructure system and promote communication and economic growth. As their primary purpose to provide a crossing for various kinds of obstacles, bridges are built in areas where conventional pathways, roads or railway constructions are unsuitable or impossible [17]. Hence, bridges are located in the most challenging environments such as canyons, mountains, crossing over valleys and rivers, and even spanning seas and connecting countries [17]. The environmental conditions of these locations, such as very low temperatures and extreme humidity, can constitute a heavy impact on bridges.

During their lifetime bridges are in general exposed to a variety of aggressive influences, such as ”varying loading and vibration, extreme weather conditions, the presence of chlorides in de-icing salts and cycles of freeze and thaw, plus chlorides in coastal areas” [17]. As bridges are affected by a number of external deterioration mechanisms originating from environmental influences, they are in particular exposed to heavy traffic loads. Bridge decks become subject to many millions of load cycles during their service life. Average daily traffic (ADT) and average daily truck traffic (ADTT) can vary a great deal from bridge to bridge, ranging from 200,000 up to two million trucks per year [18].

Along with the lack of sufficient financial resources, the combat of severe long-term deterioration is the most serious problem bridge owners have to face [12]. A leading factor causing deterioration of concrete bridge decks are cracks in the concrete. Due to these cracks, water may penetrate into the inside of the concrete slab, resulting in corrosion of the reinforcing steel. An important and enhancing role in the corrosion process is the presence of de-icing salts which are put down on bridge roadways during the winter season. Spalling and potholes are a common consequence, which may result in a reduction of structural integrity [9].

Modern bridges are often designed for a service life of about 120 years. This estimation is made under the requirement of permanent corrosion protection [19]. In most cases maintenance, repair and replacement of the superstructure are required due to gradually developed deterioration of the bridge deck over time. Large-scale cracking and wide potholes in the bridge deck are a common result of deterioration, that jeopardizes serviceability and safety. It is therefore of great interest to obtain a comprehensive understanding of deterioration mechanisms and thus apply efficient resistance and treatment methods to improve the durability of bridges [18].

2.2.1 Description of Concrete Bridge Deck Deterioration.

In a research by Li and Zhang in [18], concrete deck deterioration is described as a five-step process, ultimately resulting in a strength loss and finally the failure of the deck. In the first step, tensile stresses due to shrinkage and changes in temperature, cause cracks to arise on the bottom surface of the concrete deck in transverse direction to the bridge's lanes [9] [18]. Usually, these cracks develop when the stresses are combined with stresses due to traffic loads, but in some cases, the tensile stresses due to shrinkage and temperature changes are even high enough to cause cracking in the bottom face of the deck [18]. In the second step, transverse cracking occurs on the upper surface of the deck, while longitudinal cracks start to form on the bottom side. The in the previous stage formed cracks on the bottom side cause the slab to lose load transmission in longitudinal direction on the bottom face, resulting in flexural cracks in longitudinal direction. Altogether, these cracks form a network of cracks on the bottom side of the deck [18]. The third step is characterized by water penetrating into the formed cracks, running down to the steel reinforcement and causing the steel to corrode. The formed cracks are progressively enlarged by the long-term traffic loads on the bridge deck [9] [18]. A followed loss of interlocking, in the fourth stage results in a failure of load transmission in the longitudinal direction, which causes the deck to change its load-bearing effect. Originally behaving as a plate, the deck now acts as several separated transverse beams [18]. The deterioration process is accelerated, as water continues to intrude into the cracks, further corroding the steel rebars [9]. In the fifth and final stage, a considerable amount of steel reinforcement has been corroded away, which leads to a loss of shear capacity for fatigue strength. The result is spalling of concrete and eventually an impairment of the bridges functional capability [18].

2.2.2 Causes and Consequences of Bridge Deterioration

Structures made of reinforced concrete, such as bridge decks, have to suffer from the influence of many deterioration mechanisms throughout their lifetime. Critical factors that impair their functional capability include the impact of stresses due to freeze-thaw cycles, overloading, and fatigue [20]. The major cause for deterioration of reinforced concrete structures, however, is corrosion of the reinforcement due to chloride attack [12].

The spreading of de-icing salts during the winter is the major cause for the corrosion of reinforcement [20]. As cars and trucks drive on the bridge's roadway, deicing salt particles are sprayed into the air. How far the formed salt water is sprayed within this procedure, depends on the type of vehicle and its speed. Also the wind and the density of traffic contribute to the range of the sprayed salt water droplets, which can land up to 50 feet away from the roadway. In the area bounded by this distance, the concentration of chlorides is usually very high. In cases of high traffic density, affected areas from chlorides due to deicing salts, have been found even at a distance of more than a mile away from the respective roadway [19]. Critical areas affected by corrosion are all surfaces exposed to strong humidity and/or de-icing salts. Especially on horizontal surfaces under the edge of bridge decks, de-icing salts commonly accumulate. Pitting corrosion of the steel is a frequent consequence of de-icing salts. Typical surfaces suffering from severe pitting corrosion are often found under expansion joints [19].

The corrosion process usually starts to take place with chloride penetrating into the concrete. Through the porous concrete, the chloride ions are intruding and spreading. Existing cracks on top of the concrete deck accelerate this process. Eventually, the chlorides cause the steel reinforcement to corrode [12].

The corrosion in reinforced concrete bridge decks occurs mainly as carbonation or pitting corrosion. By the color of the resulted rust, bridge engineers can distinguish which corrosion process occurred. While carbonation results in rust in a color of more brownish tones, chloride-induced corrosion appears to leave behind a more blackish rust [20]. Depending on the environment of the respective bridge, the rate of corrosion of the reinforced concrete can vary significantly [12]. Factors such as the temperature, humidity, pH-value of the water, as well as the presence of pollution and salt, have an impact on the degree of corrosion. Varying conditions of wetness and dryness are also an accelerating factor [20].

A long-term corrosion process in reinforced concrete bridges can lead to a reduced steel cross-section area, following in a loss of shear and moment capacity [12]. In general, the occurrence of corrosion initiates several other deterioration processes to take place such as cracking, spalling and scaling [12]. These processes are shortly described in the following paragraphs.

Cracking

Cracking appears in every direction of the concrete deck, whether transversely, longitudinally or diagonal. Due to increasing stresses on the top reinforcement of the concrete deck, transverse cracks are formed on the upper surface of the deck. The rise of stresses is caused by shrinkage due to varying degrees of drying throughout the slab. Also, in the course of corrosion, the reinforced bars start to expand, leading to an increase of internal stresses [20]. The formed crack networks can give information about the loading the bridge was being exposed to. According to Steinkamp "transverse crack patterns on poured-in place concrete bridges also reflect the live-load and dead-load stresses that exist in negative or positive moment areas".

Bridges made of solid slabs which generally do not consist of beams or girders, a more prone to longitudinal cracking. In these cases as well, the main reason is shrinkage due to varying degrees of drying throughout the slab, due to inadequate curing procedures [21]. Pattern cracking is more apparent on the surface and is caused by fast, drying shrinkage at an early stage, as a result of poor curing methods [21].

Spalling

Within the process of spalling parts of the concrete on the surface starts to decompose and separate, causing a depression. This often leaves part of the underlying reinforced bars visible and vulnerable to severe corrosion. Spalling can either be initiated in the concrete or the reinforcement and is in general a result of several possible chemical reactions, such as the reaction of calcium chloride with concrete, sulfate attack on concrete, chloride penetration to steel and carbonation. Depending on the environmental conditions, these reactions can be less or more intense and fast [22].

Scaling

The deterioration of concrete surfaces caused by frequent freezing and thaw cycles or the by the effect of salt solution in the concrete is called scaling. During this process accumulated water in the concrete pores start to freeze under decreasing temperatures. With the resulting expansion of the water by about 9 percent, hydraulic pressures cause the concrete surface to scale [21]. The presence of chlorides is highly accelerating this process [17]. Also a high water-cement ratio, due to highly wet mixes or a sprinkling of water during the curing process, are further causes for scaling [21].

2.3 Preventative Design and Maintenance

Preventive maintenance measurements are recommended to be applied as soon as bridges are open to traffic. Their application at an early stage constitute a major contribution to achieve a maximum service life and can save a lot of financial resources that otherwise would be necessary for repair actions at a later time. Early maintenance is therefore not just a way to extend the service life of a bridge, but also an effective method to save money. Even simple regularly cleaning work such as the removal of dirt, debris and de-icing chemicals from the deck and around the bearings can make a big difference [21].

The design and construction of bridges underwent many adjustments over the years, such as the increasing of the concrete cover to the upper reinforced bars up to two inches, in order to reduce cracking near the reinforcement. If cracking appears in spite of this, the increased concrete cover does still decrease the probability of the cracks to reach the reinforcement. Another change that was made over the years is the placement of # 3 bars on top of the upper concrete slab stress steel to further minimize cracking [21].

Corrosion of steel reinforcement is one of the major factors of concrete deck deterioration. The use of various steel coatings such as epoxy, galvanized or metallic clad are common methods to slow down the deterioration process of the deck. More advanced and innovative ways to effectively combat reinforcement corrosion are for example the use of high-grade steel or fiber reinforced polymers (FRP). Another operation, that has shown to help to slow down deck deterioration is the installment of deck protection systems [9].

A cautionary example for the lack of proper maintenance is the Lake View Drive Bridge collapse in Pennsylvania, where severe deterioration of the concrete and reinforcement eventually resulted in the collapse of the bridge [22].

2.3.1 Preventative Design

The prevention and limitation of serious deterioration start with the design of a bridge. An adjustment in the design of material properties and structural configuration are possible steps to limit future deterioration [22].

To strengthen the concrete and make it less vulnerable to deterioration, a variety of admixtures can be added during the mixing procedure. In the ACI 2138-11, it is recommended to use "fly ash, natural pozzolans, silica fume or ground-granulated blast-furnace slag" in order to prepare concrete structures for "moderate or severe sulfates exposure" [22]. The use of fly ash as an admixture, for instance, brings several advantages to the concrete, such as an increase in strength and a reduced probability for corrosion. Further positive effects can include the protection against sulfate reaction and a reduced permeability of the concrete. The best way to protect the concrete against deterioration, however, is a high-quality design [22].

Another notable aspect in this matter is the installation of an adequate drainage for the bridge. This is important in particular in regions where a high rate of deicing salts is present [22]. A proper water flow by means of a drainage is an essential factor to protect the bridge structure from the attack of deicing salt solutions. Common drainage systems are for example deck drains and gutter systems. The installation of an adequate drainage is an aspect that should be taken into account at early stages of the design, to prevent any possible future issues regarding this matter. Also the location of the drainage is of importance, in order to reduce consequences to a minimum in case of a blockage of the drainage. However, connecting elements of the superstructure also carry the risk to become clogged with dirt and debris. Therefore, it is desirable to minimize the number of expansion joints and design the superstructure continuous. Furthermore, the compatibility of the used materials for the joints and the bridge elements should be considered in the design process otherwise, the transfer of moment and shear can be difficult to accomplish [22].

Increasing the concrete cover is one of the main ways to reduce the probability of reinforcement corrosion. This is in particular helpful to improve the long-term performance of a bridge in regions where the environmental conditions are an enhancing factor for steel corrosion. In ACI 318-11, guidelines and recommendations are given for an adequate concrete cover for specific types of exposures. The minimum thickness that is recommended in general is two inches. In cases of chain wear two and a half inches are recommended and in coastal regions, three inches are usually the minimum thickness [9]. However, also a detailed design and installation of the reinforcement play an important role [22].

2.3.2 Maintenance and Rehabilitation

Additional to preventative considerations in the structural design, proactive measures have to be executed regularly in order to limit long-term deterioration. As an effective tool to increase the resistance of bridges to corrosive environmental effects, epoxy coatings have been applied since the 1970's. Especially for bridges located in marine environments or being exposed to a high rate of deicing salts, the use of epoxy coated steel is well-suited to combat long-term steel corrosion and severe bridge deterioration. In combination with an adequate concrete cover, the use of epoxy coated reinforcement significantly reduces the probability of a failure of the concrete bridge deck [22].

The technological progress of the past years paved the way for the development of more advanced coating systems for steel bridges, leading to enhanced performances and an increased bridge service life. Various coating systems have been designed based on their needs for the use in specific environments, the feasibility of maintenance actions and the probable length of time until maintenance of the coating is required.

Which coating system is right for the respective bridges dependents on several aspects. These include "the type and expected service life the bridge, local climate and other environmental conditions, constraints regarding maintenance, possibilities of surface preparation, metal spraying or galvanizing and feasibility of applying the coating" [18]. To initially apply the coating system and further be able to carry out maintenance measurements at a later time, accessibility to all respective areas is of major importance. Especially problematic are narrow gaps, hidden surfaces, and any corners that are hard to reach [19].

The speed and degree of deterioration the coating experiences, decisively depends on the coating type, the number of coating layers and the exposure conditions. Also the quality of application of the coating as well as the treatment of the respective areas before the coating is applied, are contributing factors [19].

A number of coating systems applied in practice have proved to effectively provide protection against corrosion for a period of 25 to 30 years. Poor coating systems often show porous coating layers, which facilitates the intrusion of water, oxygen, and salts. Before even signs of deterioration can be seen, the steel underneath has already been affected by the intruding substances. If treatment actions are not applied early enough and the coating has already reached a certain level of deterioration, section loss of the steel will be the consequence. Most coating systems require a repaint after about 15 to 20 years, but for areas that are particularly vulnerable, repainting should be applied more frequently [19].

A decisive factor regarding maintenance is to create a comprehensive schedule for inspections and repair measures. Common tools to reduce deterioration from the beginning are for example deck sealants and overlays. If damage or severe deterioration has already been found, patching and structural strengthening through composites are possible methods to rehabilitate the structure [22].

The selection and frequency of individual maintenance measures are generally based on the findings of periodic conducted inspections. In practice, non-destructive testing (NDT) and electrochemical testing are widely used methods to investigate existing deterioration aside from various other testing methods in the lab. Among

NDT, ground penetrating radar (GPR) and infrared thermography (IRT) are common procedures. Electrochemical testing is a useful way to gain information about the present degree of concrete corrosion and provide a prognosis for future disrepair.

In many cases of severe deterioration, comprehensive rehabilitation measures are inevitable to preserve the structural integrity of the bridge. These include for instance patching, removal of joints, and strengthening by means of composite materials. The most widely used among those methods is patching, which is characterized by the removal and replacement of concrete which has been affected by deterioration or being at risk to experience severe deterioration.

The removal of joints is a further form of rehabilitation, which is especially advisable near bearings, above abutments and piers. It is useful to minimize the use of material prone to corrosion and diminish the need for drainage. However, by removing joints, the bridge needs to be modified to a continuous structure, which involves the use of additional reinforcement and concrete. Supplementary, joints are often closed with epoxy overlays.

Bridges that have been deteriorated due to increased traffic loads, can be strengthened using composite materials, such as fiber reinforced polymers (FRP) and carbon fiber reinforced plastics (CFRP). These materials do not just exhibit a solid resistance to corrosion but are also much lighter in weight than common concrete [22].

3. METHODOLOGY

The biggest constraint in keeping America's bridges in a satisfactory condition is the lack of sufficient financial resources. The use of efficient Bridge Management Systems (BMS) is one approach to face this problem. BMS are an effective tool to improve decision making regarding bridge design, maintenance planning and the rehabilitation and replacement (MR&R) of entire bridge networks in economical respects. Most BMS are based on condition ratings, which derive from the assessment of periodic visual inspections. The condition ratings can be viewed as an indicator, which gives an approximate estimate of the degree of bridge deterioration. The effectiveness of a BMS significantly depends on the applied deterioration prediction model, which hence also greatly affects the quality of the applied maintenance management. The prediction of future bridge conditions is a complex and difficult process, due to varying traffic loads, environmental influences and bridge aging [23].

In general, there are two main approaches to perform bridge performance prediction, which are either based on bridge condition ratings or based on structural reliability. Models based on bridge condition ratings focus on bridge serviceability and rely on the information gained by periodic visual inspections. They can further be divided into three categories, namely deterministic models, stochastic models, and artificial intelligence models [12].

The first applied bridge deterioration models in BMS were deterministic models. Deterministic models operate with simple mathematical or statistical functions. In terms of bridge deterioration modeling, these functions are used to describe the relationship between bridge element condition ratings and various deterioration factors. A commonly used deterministic model for bridge deterioration prediction is the regression model, which aims to describe the correlation between bridge condition ratings and bridge age. In this approach bridge age is the only factor affecting the bridge condition ratings. Due to their quite simple implementation and application, deterministic models are a popular approach used by bridge engineers and managers. However, a significant weakness of deterministic models is, that they are not able to consider the uncertainties which come along with the stochastic nature of the deterioration process. This limitation significantly reduces the accuracy of the model's outcomes [12].

A more advanced approach is Artificial Intelligence models, such as artificial neural networks (ANN) and case-based reasoning (CBR). ANN are computational models that aim to operate similarly to brains. According to Wang, these networks comprise a number of simple units, which operate parallel without a central control [12]. Although ANNs have been increasingly used, their application to model bridge deterioration is quite recent [24].

Far more popular are stochastic models which are characterized by their ability to consider time-varying uncertainties. Stochastic process models can be categorized into discrete time models or continuous time models. The most widely used approaches among discrete-time models for bridge deterioration prediction are Markov chain models. A Markov chain is a special type of a Markov process, which is characterized by discrete random states. The Markov chain makes several assumptions, which include uniform inspections intervals and the Markov property, which states that the future bridge condition is only dependent on the most recent condition, while all other previous conditions have no direct impact. The Markov chain model is the basis for several bridge deterioration prediction models applied in modern BMS such as Pontis and BRIDGIT. Despite the fact that Markov chain models cover several disadvantages of deterministic models and are widely used by bridge agencies for bridge deterioration prediction, the Markov chain model also has to suffer from several limitations, such as the assumption of stationary transition probabilities as well as the assumption that the future bridge condition only depends on the most previous condition, while the previous bridge condition history is neglected [12].

Since the early 1990‘s, Bayesian Networks (BN) have increased in popularity, due to their ability to handle limited input data [25]. BNs have several advantages compared to Markov models, including the ability to illustrate complex systems with many variables through a compact model structure, but most of all, BNs are able to take uncertainties into consideration by means of random variables. BNs are further characterized by their ability to easily incorporate newly observed data and update the whole network. By means of the graphical model structure that illustrates the dependencies between various variables, BNs are a useful tool to investigate causal relationships [12].

BNs that are extended with a time dimension are called Dynamic Bayesian Networks (DBN). DBNs are used to describe systems that are characterized by time-dependent variables. The computational efficiency of DBNs was demonstrated in a study by Straub in [26], in which he developed a generic framework for stochastic modeling of deterioration processes and applied it to describe the development of fatigue cracks in steel structures. Further examples include a study by Nielsen and Sorenson in [27], who applied this approach in risk-based inspection planning of offshore wind turbine foundations [25]. In the following section, a rough introduction to Bayesian networks is given.

3.1 Bayesian Networks (BN)

During the last two decades, BNs have been successfully adopted in a variety of different scientific fields to provide practical solutions for complex tasks. According to Bensi et al., a BN can be defined as “a probabilistic graphical model that represents a set of random variables and their probabilistic dependencies“ [28]. BNs use random variables to represent unknown parameters of real-world systems, and express uncertainty as a “probability distribution that reflects the relative likelihood of outcomes“ [28]. Specifically, Bayesian statistics focuses on the calculation of the conditional probability of an unknown variable given evidence. BNs are often used to verify observations and proposed theories made beforehand, based on expert opinion, engineering judgment, or physical models [28].

The foundation stone of BNs is Bayes’ theorem:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} = \frac{P(A \cap B)}{P(B)} \tag{1}$$

Where $P(A)$ and $P(B)$ are the probabilities for the occurrence of event A and B respectively, and $P(A|B)$ is the probability of event A on condition of another event B.

Bayes' theorem allows the conversion of the probability of event B given event A, into the probability of event A given event B. This theorem is the basis for Bayesian inference, which is used to investigate and determine the impact of newly observed information on the conditional probability of an event occurring.

3.1.1 Network Structure

A BN consists in general of two main components, a qualitative and a quantitative part. The qualitative part of the BN is constituted by a directed acyclic graph (DAG), which consists of a number of nodes and directed links. The nodes in the DAG represent the random variables of the respective system, while the directed links are assigned with conditional probabilities, which describe the relationship of the individual variables the links are connecting. The nodes are classified differently, depending on the direction of the link that is connecting the two nodes. A node that a link is pointing to is called "child node" or "child variable", while the node on the other end of the link is classified as its "parent node". A simple example of a BN is given in Figure 1. The nodes X_1 and X_3 are child variables, as a directed link is pointing to each of them. The node X_1, where the links are originating from, is hence their common parent variable. A node that doesn't have any links pointing to it, is called a root node, which is applicable for the node X_1 in the example. The probability of variable X_2 to be in a specific state is conditional on its parent variable X_1, therefore we write $P(X_2|X_1)$.

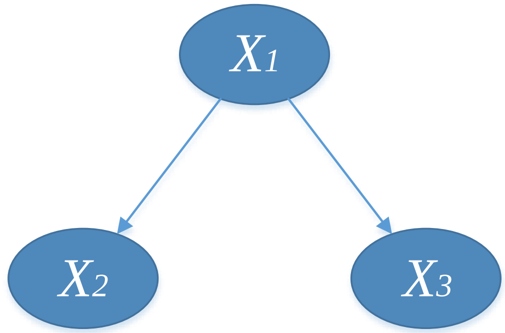


Figure 1: Sample BN with three nodes

To form a BN, every node within the DAG have to be assigned with a probability distribution. For root nodes, prior probabilities need to be specified, while for child nodes conditional probabilities are required, which are the quantitative part of a BN. The conditional probabilities describe the relationship between the individual variables. The random variables can be defined as continuous or discrete. However, in most applications, discrete random variables are used for simplification. In this case, the random variables consist of a number of mutually exclusive condition states, each assigned with a certain probability of occurrence. The conditional probabilities that define the interdependencies between parent and child nodes are stored in conditional probability tables (CPT). These CPTs need to be specified for each child node [25].

The joint probability for several variables to be in particular states is calculated by multiplying the conditional probabilities between each child variables and their respective parent variable. This is generally expressed for any given BN in equation 2.

$$P(x) = P(X1, \dots, X_n) = \prod\nolimits_{i=1}^{n} P(X_i | Pa(X_i)) \tag{2}$$

If we apply this equation to the sample BN above, the joint probability of nodes

X_1, X_2, and X_3 would be calculated as:

$$P(X_1, X_2, X_3) = P(X_1)P(X_2|X_1)P(X_3|X_1) \quad (3)$$

Where $P(X_1)$ is the prior probability of node X_1 to be in a particular state, and $P(X_2|X_1)$, $P(X_3|X_1)$ are the conditional probabilities for nodes X_2 and X_3, given the state of their parent node X_1.

3.1.2 Connection Types and D-Separation

In general, there are three different types of how variables in a BN can be connected. These connection types are the serial connection, diverging connection, and converging connection. All three types are depicted in Figure 2.

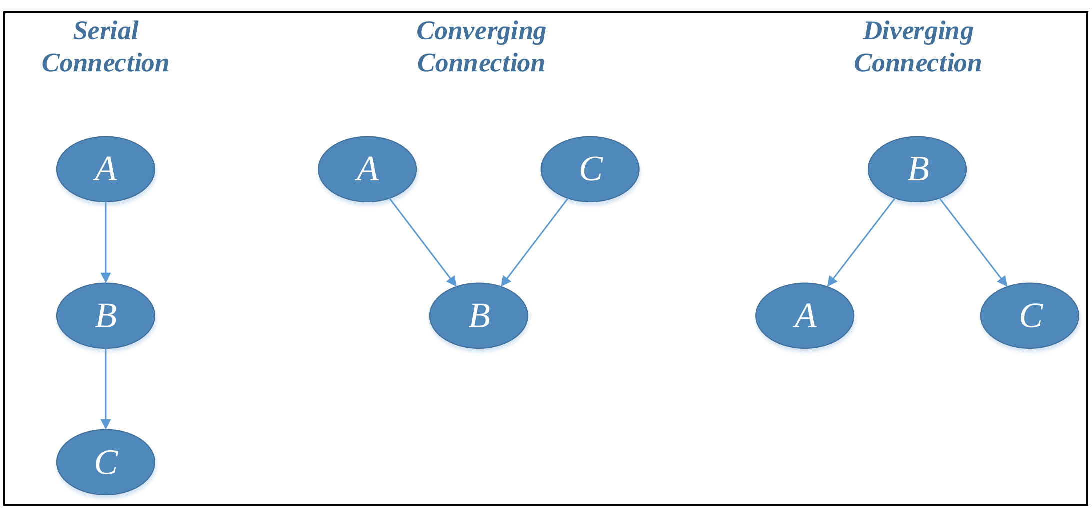


Figure 2: Connection types

In the serial connection, the variables A and B are defined as independent if the state of variable C is observed. Therefore, a change of status of variable A does not influence the current status of variable C. In the converging connection, the variables A and C are dependent if the status of variable B is known, and in the diverging connection, variables A and C are independent if the status of variable B is observed.

By means of the rule of d-separation, it can be determined whether two variables in a BN are conditionally independent. In Figure 2, the two variables A and C are considered d-separated if they are independent of one another given a third variable, B. This can be expressed as:

$$P(A, C|B) = P(A|B)P(C|B) \tag{4}$$

The d-separating variable B blocks the exchange of information between the variables A and B [28]. Depending on the fact if observation for variable B is present, the variables A and C are d-separated (blocked) or not. In the serial and diverging connection, A and C are considered to be d-separated if variable B was observed. Hence, A and C only influence each other if B is unobserved. Reversely, A and C are d-separated in the converging connection if variable B was not observed [28].

3.1.3 Bayesian Inference

One of the major characteristics of BNs is the ability to update the entire BN with newly observed data, using inference. If we, for instance, assume for the sample BN in Figure 1, that evidence for variable X_2 was observed, as illustrated in Figure 3, the state of variable X_2 is no longer unknown, which hence affects the probability for all other variables in the BN.

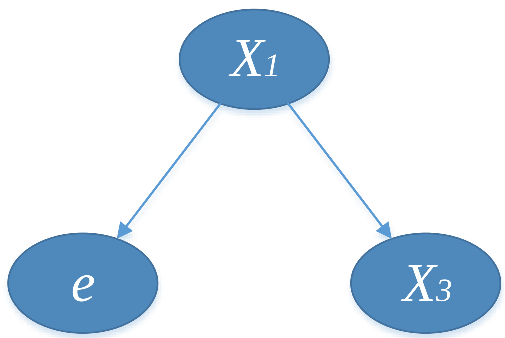


Figure 3: Bayesian inference

The new network probability will be updated as follows:

$$P(X_1, X_3|e) = \frac{P(X_1, e, X_3)}{P(e)} = \frac{P(X_1)P(e|X_1)P(X_3|X_1)}{P(X_1)P(e|X_1)} \tag{5}$$

Where e is newly observed evidence. However, it should be noted that is only suitable for rather small BNs with only a few states for every variable. In practice, various inference algorithms are used to calculate marginal probabilities for each unknown variable given a set of new observed evidence. Several exact and approximated inference algorithms have been used in the past for this purpose. Among those algorithms junction trees are the most widely applied algorithms for inference [12]. If no newly observed data is available, the calculation is done using prior probabilities. If however, new data was observed, the inference algorithm will incorporate the new data and thus update all probabilities. According to Wang, the observed data is categorized into hard and soft evidence. Hard evidence, also termed as direct observation directly relates to any specific state of a variable. Soft evidence, or indirect observation, only refers to any specific state of a variable with probability [12].

BNs are able to operate with both discrete and continuous states for the variables. The variables of most engineering systems, that aim to describe physical processes are of continuous nature. However, in most BN applications the variables are considered to be discrete since the most related inference algorithms are developed to effectively operate with discrete states only. Having said this, there are approximate algorithms, such as Markov Chain Monte Carlo (MCMC), which make it possible for the respective BN to work with continuous variables, but can also have a significant negative effect on the rate of convergence [12]. In the course of this, the random variables which initially were defined as continuous will be discretized and replaced by equivalent variables in a finite space. It is recommended to discretize the variables in order, starting from parent nodes up to child nodes. The discrete intervals in which the continuous variables are discretized should be chosen adequately. One method is to define the intervals in a way that they fit the characteristics of the associating variables (multivariate discretization). A more approximate way is to choose for all variables the same intervals (univariate discretization), which is considered to be more practical

[12].

The outcomes of a BN can, in general, be evaluated by means of three different ways: sensitivity analysis, outcomes comparison, and scenario testing. Sensitivity analysis is suitable to investigate which variables have the greatest impact on the results [12]. Another way is to compare the results with existing data, for example with information in the literature or results gained through experiments. Within scenario testing, the respective BN is modeled for different scenarios specified by experts. The goal is to determine whether the BN is behaving as expected based on previous experience and in compliance with present recognized research. To achieve a most effective evaluation of the BN, these three methods should be applied together [12].

3.2 Dynamic Bayesian Networks (DBN)

By adding a time dimension a BN can be extended to a DBN, which is a special type of a BN. Two common forms of DBNs are Hidden Markov Models (HMMs) and Kalman Filter Models (KFMs) [29]. A DBN consists of a sequence of BNs, which are defined for different points in time. Therefore a DBN could be said to be a BN that evolves over time. The model structure of the individual BNs, however, stays the same for every point in time [25]. The individual BNs are also referred to as time slices $(t_i, t_{i+1}, \dots, t_{i+n})$. Several nodes of adjacent time slices are connected through temporal directed links, which constitute probabilistic dependence similar to the links in a usual BN. If all time slices have the same model structure and identical CPTs, except for the initial time slice, the DBN is considered to be homogeneous. An example of a DBN consisting of three time slices is illustrated in Figure 4, where the red arrows represent temporal links [25]. The depicted DBN consists of three random variables $A(t_i)$, $B(t_i)$ and $C(t_i)$ associated with the time dimension t_i, which repeat over time.

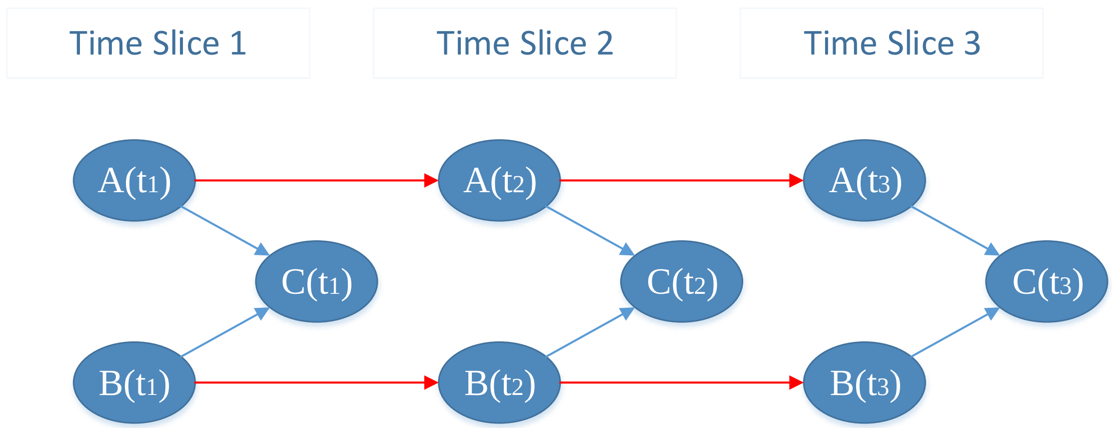


Figure 4: Sample DBN *[25]*

The probability of $P(A(t_{i+1})|A(t_i))$ is equal to $P(A(t_i)|A(t_{i-1}))$ since the DBN is considered homogeneous. Hence, the BNs at each time step are viewed as separate BNs [2]. A detailed description of DBNs, including inference and learning algorithms, was given by Murphy in *Dynamic Bayesian Networks: Representation, Inference and Learning* [29].

3.3 Estimation of Conditional Probabilities

A major aspect regarding the effectiveness of a BN is the conditional probability tables (CPT). Several kinds of sources can be used as the basis for CPT estimation, including statistic databases, expert judgment, and data derived from experiments [12]. However, the conducting of experiments might not always be practical and cost-effective [12]. Another alternative is data that can found in the literature. Although this might not be the most satisfactory method either, since it may not sufficiently relate to the variables within the constructed BN [12]. In practice, it is most common to derive the CPTs form statistical data. Many BMS hold their own database which stores various bridge information including inventory data, evaluation data, maintenance data, and inspection data [23]. This data can be used to determine the CPTs related to bridge elements by applying various learning algorithms, such as search- and scoring-based algorithms, and "Bayes Net Power Constructor" (BNPC) [23] [12]. A widely used approach is to estimate the CPTs using bridge element condition ratings where at least two successive condition ratings without maintenance in between are required. In practice, the non-linear least squares optimization method and the maximum likelihood estimation (MLE) are often used for this purpose [23]. One more alternative is the parameter estimation by means of expert elicitation, which is in general considered as the most reliable of all mentioned methods. The MLE and the method of expert elicitation are explained in sections 3.3.1 and 3.3.2 respectively.

3.3.1 Maximum Likelihood Estimation (MLE)

The Maximum Likelihood Estimation method (MLE) is a commonly applied method for estimating one or more unknown parameters from observed data. Because of its easy computation, the MLE has earned great popularity and its principle is the basis for several other more complex machine learning algorithms. In principle, the MLE seeks to find the value for the probability of an unknown parameter that makes the observed data most probable. By means of a simple example, the MLE will be explained in detail.

Consider a BN consisting of just one variable X, which represents the result of tossing a coin. The random variable X has two possible states: heads, indicated as $(X = 1)$, and tails, indicated as $(X = 0)$. The expression $\theta = P(X = 1)$ represents the probability that a coin toss will result in heads. Assume we produced training data D by flipping the coin m times and observed mh heads $(X = 1)$ and mt tails $(X = 0)$. We make another assumption stating that the results of the individual coin flips are independent and identically distributed (i.i.d.), meaning one coin toss has no influence on another coin toss, and the outcomes of all coin flips are subject to the same probability. The principle of the MLE is to find the value of θ that maximizes $P(D|\theta)$, which defines the likelihood of the observed data D given θ and is often referred to as data likelihood function. If we assume just one coin toss, resulting in $X = 1$, then we have $P(D|\theta) = \theta$. Correspondingly, if the coin toss results in $X = 0$, then we have $P(D|\theta) = (1 - \theta)$. Now if we, however, have a dataset such as $D = \{1,0,1,0,0,1\}$, the probability $P(D|\theta)$, or $P(mh, mt|\theta)$, can simply be calculated by multiplying the probabilities of each coin toss of the observed data.

$$P(D = \{1,0,1,0,0,1\}|\theta) = \theta \cdot (1-\theta) \cdot \theta \cdot (1-\theta) \cdot (1-\theta) \cdot \theta$$

$$P(D = \{1,0,1,0,0,1\}|\theta) = \theta^3 \cdot (1-\theta)^3 \tag{6}$$

In general, this can be expressed as the following equation:

$$P(D = mh, mt|\theta) = \theta^{mh} \cdot (1-\theta)^{mt} \tag{7}$$

Now having defined a formula for the data likelihood function $P(D|\theta)$, we now need to determine the derivative of $P(D|\theta)$ with respect to θ and find the value for θ that makes the derivative equal to zero. For this purpose, the logarithm $\ln P(D|\theta)$ is used since it simplifies the derivation and leads to the same result as deriving $P(D|\theta)$. The derivation process is skipped at this point and instead, it is referred to [30]. However, if the derivation is set to zero it leades to the following expressions:

$$0 = mh\frac{1}{\theta} - mt\frac{1}{1-\theta}$$

$$mt\frac{1}{1-\theta} = mh\frac{1}{\theta}$$

$$mt\theta = mh(1-\theta)$$

$$(mt + mh)\theta = mh$$

$$\theta = \frac{mh}{mh + mt} \tag{8}$$

Now we have derived the MLE algorithm for estimating the value θ that maximizes $P(D|\theta)$. The algorithm seems very intuitive. If we, for example, assume to toss the coin 100 times, and observed 55 heads $(mh = 55)$ and 45 tails $(mt = 45)$, the probability of $P(X = 1)$ would be calculated to $\theta = \frac{55}{55+45} = 0.55$. The MLE approach is very reasonable when a great number of training data is available.

3.3.2 Bridge Expert Elicitation

A way to estimate the CPTs directly is to consult bridge maintenance engineers that have long-term working experience and a consequential extensive expertise in terms of bridge deterioration. Since these experts have proved their expertise in practice, it is reasonable to derive parameters based on their judgment. The elicitation process can be defined by five steps, which include "experts selection, expert training, question preparation, expert judgment elicitation and results verification" [31]. In the first step, several bridge engineers have to be selected, with regard to sufficient working experience and the required technical knowledge. After the engineers have been selected, they should be trained in the second step, in order to be able to adequately assess the probabilities. The third step consists of the preparation of questions for the experts [23]. Great importance should be paid to the design of the questions for the elicitation process. The questions should be designed in a way that subjectivity in the expert's judgment is minimized. In the next step, the actual expert elicitation takes place and is then followed by the fifth and last step, which is the verification of the given expert's answers to ensure that any incorrect answers are excluded. If the bridge engineers give answers in form of exact numbers, the CPTs can directly be specified based on these numbers. However, bridge maintenance engineers are not always able to provide exact numbers, but rather give short answers in textual form. Hence, in this case, it is reasonable to ask the engineers for their estimates on a scale, which further can be converted into numerical values [23]. Especially for complex BNs, the use of expert knowledge facilitates the estimation of CPTs significantly [12]. A disadvantage however is, that expert judgment always includes the risk of a certain degree of subjectivity [25]. Also, in cases where the BN consists of a large number of variables and states, the determining of the CPTs through the use of expert knowledge might be very difficult [25].

4. NATIONAL BRIDGE INVENTORY DATA ANALYSIS

One aim of this study is to investigate which environmental and design factors influence the deterioration of Rhode Islands bridges the most. For this purpose, several parameters of the National Bridge Inventory (NBI) were selected to examine whether correlations exist between the chosen parameters and the deterioration of the three bridge elements, deck, superstructure, and substructure. The implementation of this aim was inspired by two similar studys by Frühauf [32] and Cruz [9]. For each bridge element deterioration rates were computed using the condition ratings of the inspection records in the NBI. The inspection records in the NBI are annually provided by the Federal Highway Administration (FHWA) and are freely available on the FHWA homepage [33]. They can be downloaded as text files for each state and each year. The formatting of the files is defined in the *Recording and Coding Guide for the Structure Inventory and Appraisal of the Nation's Bridges* [5].

Before the data was used for correlation analysis, the data needed to be filtered in order to exclude unreliable and incorrect data. The data filtering process along with a description of all filters is described in section 4.1. In section 4.2 it is explained how the deterioration rates were computed, and in section 4.3 possible correlations between the selected parameters and the respective bridge elements are analyzed.

4.1 Data Filtering

4.1.1 Filters

The FHWA started recording the results of periodic bridge inspections in 1992, so files for 26 years in total (1992 to 2017) could be obtained from the NBI database. In order to obtain reliable data for the computation of the deterioration rates and further the parameter estimation of the deterioration models, several filters were used to sort out incorrect and unusable data. These filters are listed below and are described in more detail in the following paragraphs.

- Culverts
- Insufficient Inspection Records
- Invalid Inspection Intervals
- Missing Data
- Incredible Data

Culverts

Since culverts are not considered in this study, the data of the respective structure IDs had to be removed from the obtained data sets. To identify the culverts, NBI item #43B Structure Type was used, which assigns each bridge with one of 23 different structure types.

Insufficient Inspection Records

In order to be included, it was decided that bridge IDs had to show at least 4 consecutive inspection records. Hence, all bridges built after 2013 were removed from the datasets.

Invalid Inspection Intervals

Bridges should usually be inspected at least every two years. To check if this directive has been met over the years, NBI item #90 inspection date has been used. In this item, the month and year of the most recent conducted inspection are recorded, but only the year was considered. To calculate the inspection interval for each year the current inspection date was subtracted from the inspection date of the year before. After that, the average inspection interval was calculated for each bridge ID. As stated above, bridges should be inspected at least every two years, therefore it was originally planned to remove all bridge IDs which show an average inspection interval greater than two years. However, when analyzing the database it has been shown that more than 20% of all bridges in Rhode Island had an average inspection interval greater than two years. Hence, in order to be able to use a sufficient amount of data, it was decided to increase the limit for the inspection interval to 2.5 years, this way the number of neglected bridges due to too large inspection intervals decreased to less than 1%.

Missing Data

The datasets for the considered NBI items showed a large number of missing values. About 18% of all entries for years 1992 to 2017 were being observed to be blank. It should be mentioned that this count also includes bridges that were built after 1992, and hence could obviously not provide data before their year of construction. However, these bridges were observed to constitute just a small number. Correspondingly to filter invalid inspection intervals, it was decided that bridge IDs had to provide at least 4 consecutive years without missing data to be included.

Incredible Data

When analyzing the NBI data, small inconsistencies in the datasets could be found, which raised concerns about the credibility of the respective data entries. An in-depth inspection of the NBI data was done in order to search for these inconsistencies within the datasets for all considered NBI items. For instance, bridge ID 2430 showed constant values of 6 for item lanes on structure #27 between year 1995 and 2013. However, from year 1992 to 1994 the bridge showed a very unusual value of 24, which was probably an error in the database. Furthermore, for years 2014 to 2017, the bridge was assigned with 4 lanes, although no information could be found in other NBI items that the bridge was reconstructed or was subject to major maintenance measures that increased the number of lanes on structure. Due to these varying values, the bridge was removed from the dataset. Particularly affected by such small inconsistencies were the condition ratings for the bridge elements. Here, the most probable reason for unusual entries is subjectivity from different bridge inspectors.

Consider for example bridge ID 4860, which shows the following superstructure ratings for 12 consecutive years: 6, 6, 6, 6, 6, 7, 7, 6, 6, 6, 6, 6. The two ratings of 7 are most likely a result of the subjectivity of the bridge inspectors. As stated earlier bridges are most of the times only inspected every two years. Therefore the second rating of 7 is probably just adopted form the inspection record of the year before, and thus both ratings are the result of just one inspection. To check this statement NBI item #90 inspection date was examined for the respective entries of the condition ratings. In such cases, the respective incredible data entries were adapted to fit the surrounding data.

4.1.2 Filtering Process

The filters that are described above, were applied one after the other. The filtering process, along with the number of removed bridge IDs and the number of remaining bridge IDs after each filtering step, is summarized in Table 2.

Since bridges have been removed and added in the NBI over the years, the first task was to determine how many different bridge IDs have been listed in the NBI until 2017. A total of 898 different structure IDs could be observed in all combined inspection records from year 1992 to 2017. After the application of the first three filters, each NBI item that has been selected for the deterioration models was checked for missing and incredible data. All filtered birdge IDs are listed in Appendix B – List of removed bridge IDs after filtering, while all used bridge IDS can be found in Appendix A - List of approved bridge IDs after filtering.

Number of available bridge IDs before filtering		898
Filter	**Number of excluded structure IDs**	**Number of remaining structure IDs**
1. Culverts	49	849
2. Insufficient Inspection Records	32	839
3. Invalid Inspection Intervals	18	820
4. Missing and/or Incredible Data	226	**573**

Table 2: Filtering process

4.2 Calculation of Deterioration Rates

After the obtained data had been filtered, the data was used to calculate deterioration rates for each bridge element (deck, superstructure, and substructure) using the bridge element condition ratings in the NBI. A deterioration rate as calculated in this study indicates the average change of condition rating over the period of one year. As an example, a deterioration rate of -0.125 would indicate that a bridge would decrease its condition rating, and hence deteriorate, by 12.5% within one year. This would mean that for example, a bridge with this deterioration rate and a condition rating of 7 (good condition) would take 8 years to decrease to a condition rating of 6 (satisfactory condition).

Table 3 shows an extract of the bridge deck condition ratings for several bridge IDs. As can been seen, the condition ratings do not always decrease, as initially expected, but also increase, which indicates an improvement of the respective bridge's condition. Such improvements are most likely the results of applied maintenance actions, but could also be a result of inspector subjectivity, as previously mentioned in 4.1.1.

Bridge ID	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
500	7	7	6	6	6	6	6	6	6	6	6	6	6
540	7	6	6	6	6	6	6	6	6	6	6	6	6
550	7	7	5	5	5	5	5	5	5	5	7	7	7
560	7	8	8	8	8	8	8	7	7	7	7	7	7
580	7	7	7	7	6	7	7	7	7	7	7	7	7

Table 3: Extract of NBI deck condition ratings

However, since the aim of this study is to investigate natural working bridge deterioration, transitions to an increased condition rating were not considered in the computation of the deterioration rates. The computation of the deterioration rates is further explained by the condition rating history of a sample bridge ID, as depicted in Figure 5. As can be seen, the bridge shows overall a decreasing rating behavior, except between years 2001 and 2002, where the bridge experienced a maintenance action, which leads to an increase in the condition rating. Inbetween years 1992 and 2001 the bridge experienced a decrease of 2 ratings, decreasing from a rating of 7 to a rating of

5. In year 2001, the bridge was subject to maintenance actions which improved the bridge's condition and caused the rating to increase to a rating of 8 in the following year. After that, the ratings stayed constant for 5 years, then decreasing again to a condition rating of 5 in year 2015.

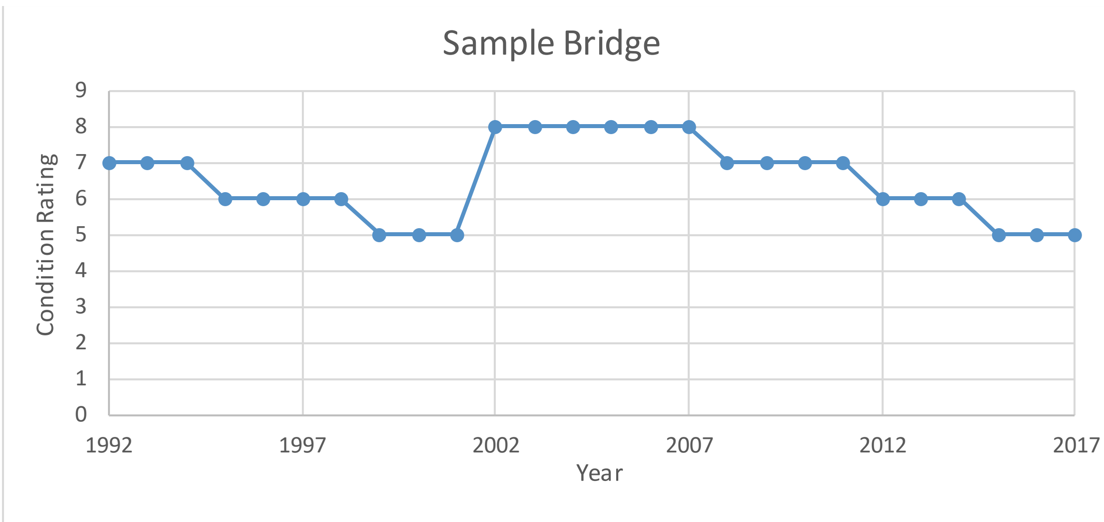


Figure 5: Sample development of bridge condition ratings

Now, to calculate the deterioration rate the condition rating history was divided into several time periods, which are characterized by at least one decrease in rating and no increase. For each time period, a deterioration rate was calculated, which is the total difference in rating divided by the difference in years of that time period. The final deterioration rate is computed by calculating the average of all deterioration rates of each time period. For instance, applying this approach to the example above, two time periods can be used. For the first time period, from 1992 to 2001, the deterioration rate would be calculated as $-\frac{7-5}{2001-1992} = -0.222$, and for the other time period, the deterioration rate would be calculated to $-\frac{8-5}{2017-2002} = -0.2$. The final deterioration rate would then be calculated to $-\frac{0.222+0.2}{2} = -0.211$.

Special attention was paid to time periods at the beginning and end of the available bridge condition rating datasets. Consider for example the following set of condition ratings, as shown in Table 4. As can be seen, the bridge starts with a rating of 6 in 1992, then instantly decreasing to a rating of 5 in 1993, and decreasing again in 1999 to a rating of 4. In 2002 the rating went up to 7, where it remained constant for five years. After that, the rating decreases two more times, in years 2008 and 2013. Following the approach as stated above, two time periods could be used, from 1992 to 2001 and 2002 to 2017. Now for the first time period, the deterioration rate would be calculated to $-\frac{2}{9} = -0.222$. However, the problem with this period is, that there is just one rating of 6 in the initial year of 1992. Intuitively, the bridge was very likely in a rating of 6 for several more years before it changed to a rating of 5 in 1993. This intuition is also supported when looking at the development of the ratings in the second time period, where all ratings stayed constant for at least five years. Therefore, since no information is available of how long the bridge was in rating 6 before year 1992, this respective year was neglected and the deterioration rate for the first time period was calculated to $-\frac{1}{9} = -0.111$.

ID	92	93	94	95	96	97	98	99	00	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17
60	6	5	5	5	5	5	5	4	4	4	7	7	7	7	7	7	6	6	6	6	6	5	5	5	5	5

Table 4: Sample for invalid condition ratings for calculating deterioration rates

Also, in cases where a bridge showed inconsistently or contradicting deterioration behavior, the respective bridge was neglected from the computation. Consider for example the following condition ratings as depicted in Figure 6. All time periods that would fulfill the before mentioned requirements are not longer than 4 years. Since bridges are most of the time inspected only every two years, most likely just two inspections were conducted within those time periods. Further, the bridge shows unusual drops in the condition ratings, as for example between years 2005 and 2006, where the bridge sharply falls from a rating of 6 to a rating of 3. Due to this incredible development in the condition ratings, this bridge would not be taken into consideration.

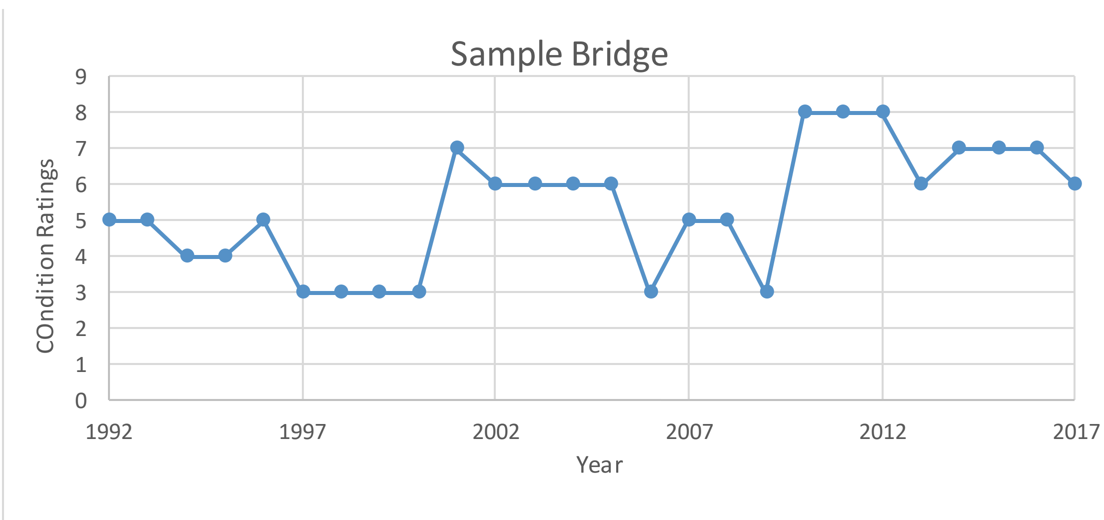


Figure 6: Inconsistent deck condition ratings

4.3 Correlation Analysis

After having computed the deterioration rates for each bridge ID, the deterioration rates were then set into relation with several selected parameters of the NBI to look for any possible correlations. As mentioned earlier, deterioration rates were calculated for bridge deck, superstructure, and substructure. Therefore, the analyzing process was divided into three sections, each for one of the bridge elements. In Table 5 and Table 6, all selected NBI items are listed, which were divided into time-independent and time-dependent parameters.

Time-independent parameters
#26 Functional Classification of Inventory Route
#27 Year Built
#28A Lanes on Structure
#31 Design Load
#42A Type of Service on Bridge
#43A Kind of Material and/or Design
#43B Type of Design and/or Construction
#45 Number of Spans
#48 Length of maximum Span
#49 Structure Length

Table 5: Investigated time-independent NBI items

Time-dependent parameters
#29 Average Daily Traffic (ADT)
#109 Average Daily Truck Traffic (ADTT)
#58 Deck Condition Rating
#59 Superstructure Condition Rating
#60 Substructure Condition Rating

Table 6: Investigated time-dependent NBI items

For each bridge element, an excel spreadsheet was created which stores the computed deterioration rates for all considered bridge IDs along with associating values for the time-independent and time-dependent parameters listed in Table 5 and Table 6. The excel spreadsheets were then imported into MatLab to create several graphs, which help to visualize and analyze any possible correlations between the bridge element deterioration rates and each parameter. To effectively illustrate the correlations different kinds of graphs were used. For parameters that are characterized by categorical data such as functional classification, design load or structure kind, box plots were created, while for continuous parameters, such as structure length or ADT scatter plots were generated. Furthermore, for categorical parameters, Spearman's rank correlation coefficient was computed, while for continuous parameters Pearson correlation coefficient was computed. Both coefficients are a measure for the strength of correlation between two variables.

4.3.1 Deck

Before investigating any correlations between deck deterioration and the selected parameters, a histogram was generated which shows the frequency of all computed deterioration rates. As can be seen in Figure 7, most bridges showed a deterioration rate between -0.02 and -0.04 (152 bridges, 33,85%). The next most frequent deterioration rates were settled in between -0.07 and -0.08 (102 bridges, 22,72%). When looking at the diagram it is noticeable that much fewer bridges had deterioration rates in between those two ranges.

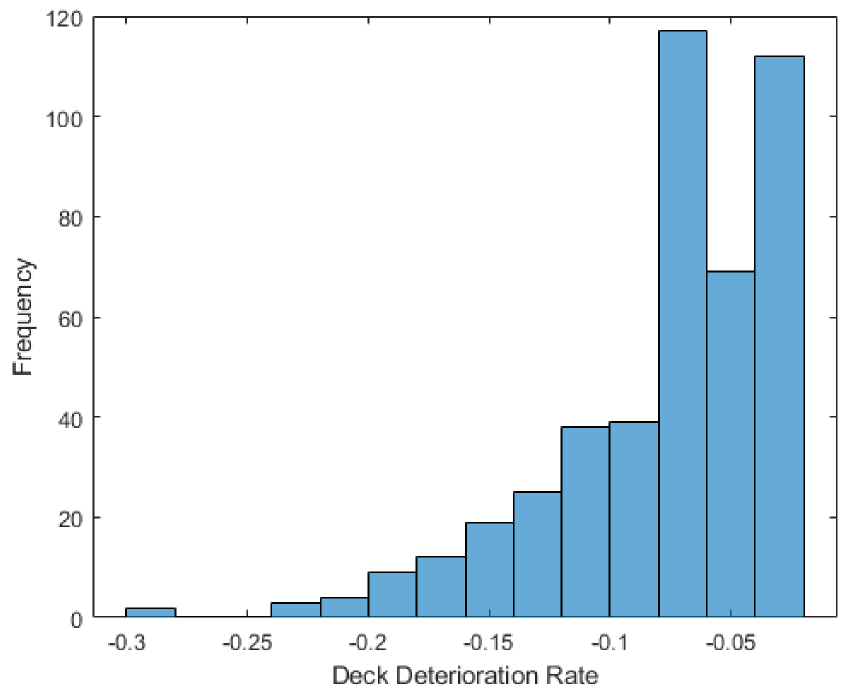


Figure 7: Deck deterioration rates frequencies

After the peak around -0.07 the frequencies for the deterioration rates are continuously decreasing with higher deterioration rates. The greatest computed deterioration rate is -0.289, while the average deterioration rate for bridge deck is -0.072.

Correlations between deck deterioration and time-independent parameters

In this section, the graphs and correlation coefficients that were generated to investigate correlations between deck deterioration rates and time-independent parameters are presented. The computed correlation coefficients are shown in Table 7 and Table 8. As can be seen, no significant correlations between the deterioration rates of element bridge deck and the selected parameters are indicated. This was also supported when analyzing the created graphs. The generated scatter plots and box plots can be found in Appendix C – Figures for bridge deck correlation analysis.

Categorical time-independent parameters	Spearman correlation coefficient
Functional Classification	-0.0423
Lanes on Structure	0.0289
Design Load	0.08047
Type of Service on Bridge	-0.0758
Kind of Material and/or Design	0.1172
Type of Design and/or Construction	-0.0999
Number of Spans	-0.1559

Table 7: Spearman correlation coefficient for deck deterioration rates vs categorical time-independent parameters

Continuous time-independent parameters	Pearson correlation coefficient
Structure Length	-0.0306
Length of maximum Span	0.1149
Year Built	0.1535

Table 8: Pearson correlation coefficient for deck deterioration rates vs continuous time-independent parameters

However, although no strong correlation could be observed, the created graphs for parameters year built, lanes on structure, structure kind, and structure length are shown in the following paragraphs to give an insight in the results.

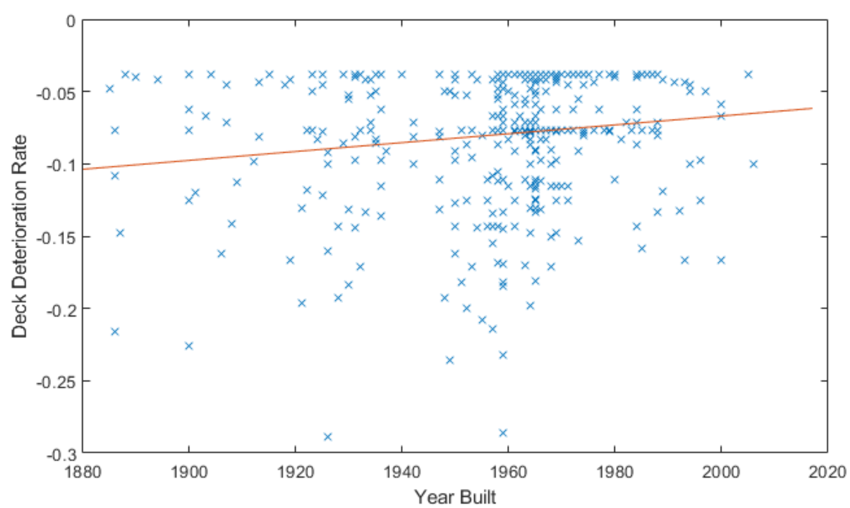


Figure 8: Correlation between deck deterioration rate and year built

Figure 8 shows the scatter plot for the correlation between deck deterioration rates and NBI item year built. The graph shows that most bridges were built between 1960 and 1970, and most have a deterioration rate between -0.03 and -1.2. Although the slope of the plotted regression line is very low, it still indicates that the deterioration rates for bridge deck are greater the older the bridge is. However, as can be seen, there are also some bridges built around 1880 with deterioration rates of -0.05 or lower, and therefore do not fit with this pattern.

Figure 9 shows the box plot for parameter lanes on structure, in which the blue straight line shows the average deck deterioration rate. When looking at the diagram no correlation can be observed. One would expect that bridges with a higher number of lanes would deteriorate faster, but the created box plot does not support this hypothesis. Bridges with 2, 3, 4 and 5 lanes on structure show a very similar median deterioration rate, while the median deterioration rate for the rest is much slower. At this point it should be noted that there is just a small number of bridges with 1, 6, 7, 8 and 10 lanes on structure, so the box plot is not very meaningful for those bridges.

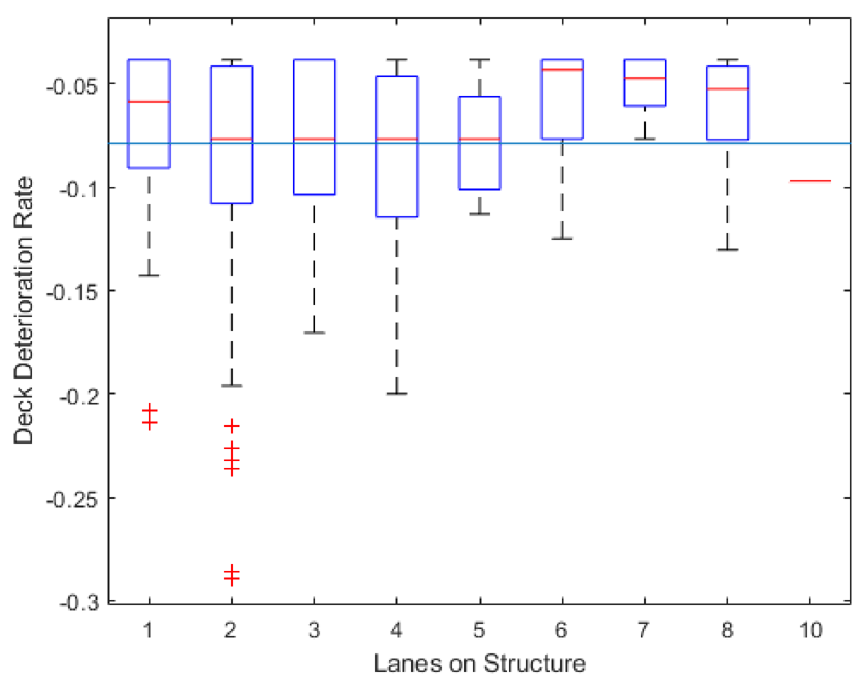


Figure 9: Box plot for deck deterioration rate vs. lanes on structure

Shown in Figure 10 is the box plot for deck deterioration rate in relation to different structure kinds. The median deterioration rate for categories 1 (concrete), 2 (concrete continuous), 3 (steel), and 5 (prestressed concrete) are very similar. Category 7 (wood or timber) shows by far the greatest median deterioration rate, while category 4 (steel continuous) shows the lowest.

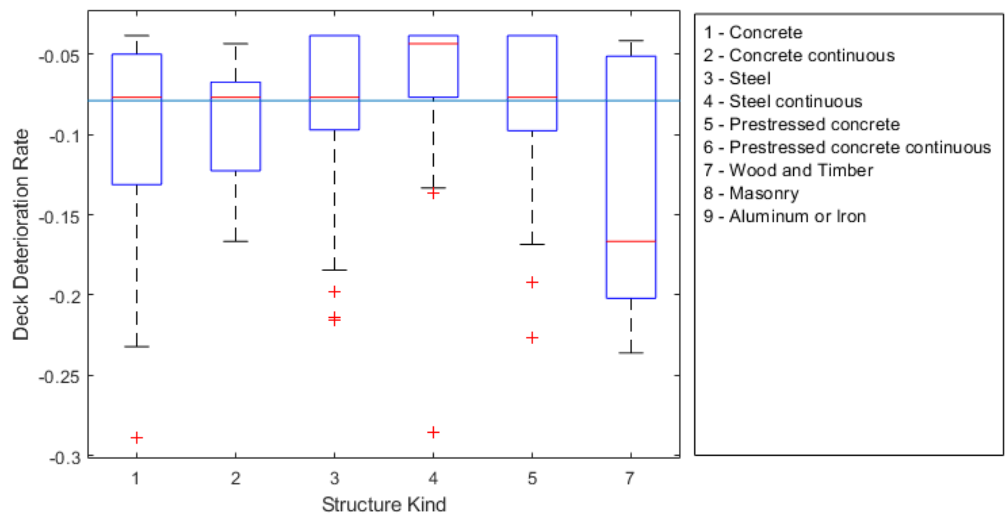


Figure 10: Box plot for deck deterioration rate vs. structure kind

In the next box plot in Figure 11, the relation of deck deterioration rate versus structure length is depicted. The plotted regression line indicates that the deterioration rate goes up with increasing structure length, as one would expect. However, the slope of the line is very low and thus not very meaningful. As can be seen, most bridges are less than 100 meters long. The deterioration rates for most of these bridges is between -0.03 and -1.2, as it was for year built.

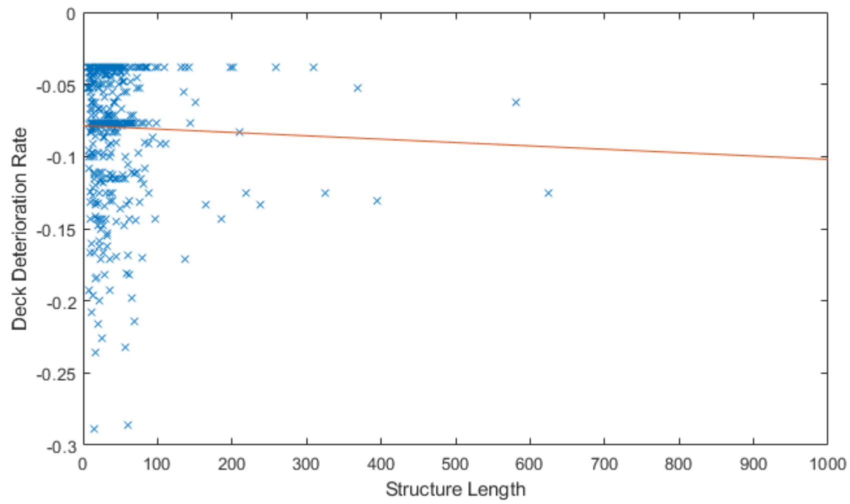


Figure 11: Correlation between deck deterioration rate and structure length

Correlations between deck deterioration and time-dependent parameters

In this section correlations between the time-dependent NBI items ADT, ADTT and the condition ratings of all three bridge elements were investigated. Instead of using the calculated deterioration rates, the condition ratings from the NBI were used directly to compute a linear correlation between the deck condition ratings and each parameter, since the calculated deterioration rates are constant and therefore less suitable as the reference factor in this case. An excel spreadsheet was created for each pair of parameters that were investigated, as it was done for the time-independent parameters. If in the spreadsheets with ADT and ADTT any cells for a specific bridge ID in a specific year was containing a zero, the respective cells were deleted, so that these zeros did not distort the correlation calculation. For the analysis scatter plots were created to compare the individual parameters with the deck ratings. Table 9 and

Table 10 show the correlation coefficient between deck rating and the considered time-dependent parameters for continuous and categorical parameters respectively.

As can be seen, the correlation coefficients for ADT and ADTT between deck rating are both very low. However, odd is that the correlation for ADTT is much greater than the correlation for ADT. The scatter plots for both parameters can be found in Appendix C – Figures for bridge deck correlation analysis.

Continuous time-dependent parameters	Pearson correlation coefficient
Average Daily Traffic (ADT)	-0.0319
Average Daily Truck Traffic (ADTT)	0.1149

Table 9: Pearson correlation coefficient for deck deterioration rates vs continuous time-dependent parameters

Categorical time-dependent parameters	Spearman correlation coefficient
Superstructure Condition Rating	0.5105
Substructure Condition Rating	0.4291

Table 10: Spearman correlation coefficient for deck deterioration rates vs categorical time-dependent parameters

The strongest correlation that could be found in this category is between the deck condition rating and the superstructure condition rating. The associating scatter plot is illustrated in Figure 12. The correlation between deck rating and substructure rating is very similar, although a little weaker. The associating scatter plot can be found in Appendix C – Figures for bridge deck correlation analysis.

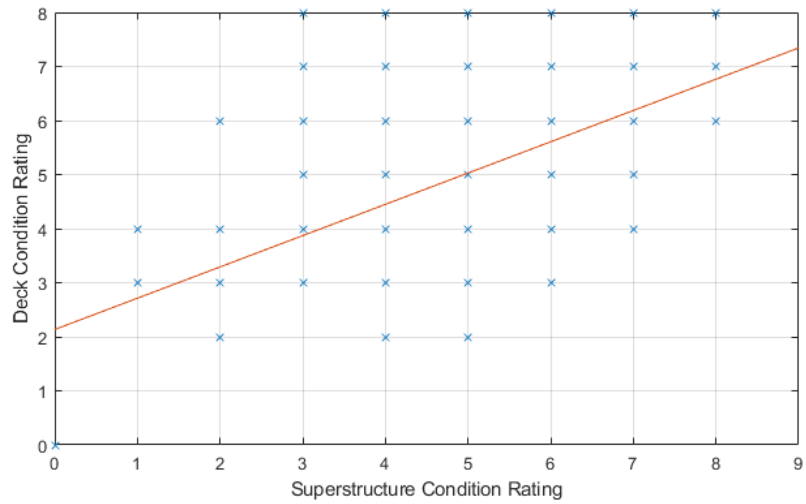


Figure 12: Correlation between deck condition rating and superstructure condition rating

4.3.2 Superstructure

The correlations between superstructure and the selected parameters were analyzed the same way as for bridge deck. At first, the frequencies of the deterioration rates for superstructure were plotted in a histogram, as shown in Figure 13. Compared to the histogram for bridge deck, the deterioration rates for the bridge superstructure are overall a little greater. The histogram shows three peaks. Most of the analyzed bridges have a superstructure deterioration rate between -0.02 and -0.03 (91 bridges, 18,24 %), followed by the range between -0.06 and -0.07 (114 bridges, 22.85 %), and then the range between -0.09 and -0.1 (83 bridges, 16.63 %). These bridges constitute 57.72 % of all 499 considered bridges. The average deterioration rate is -0.089, which is a little higher than the one for bridge deck. However, the greatest deterioration is -0.217, which is less than the highest for bridge deck.

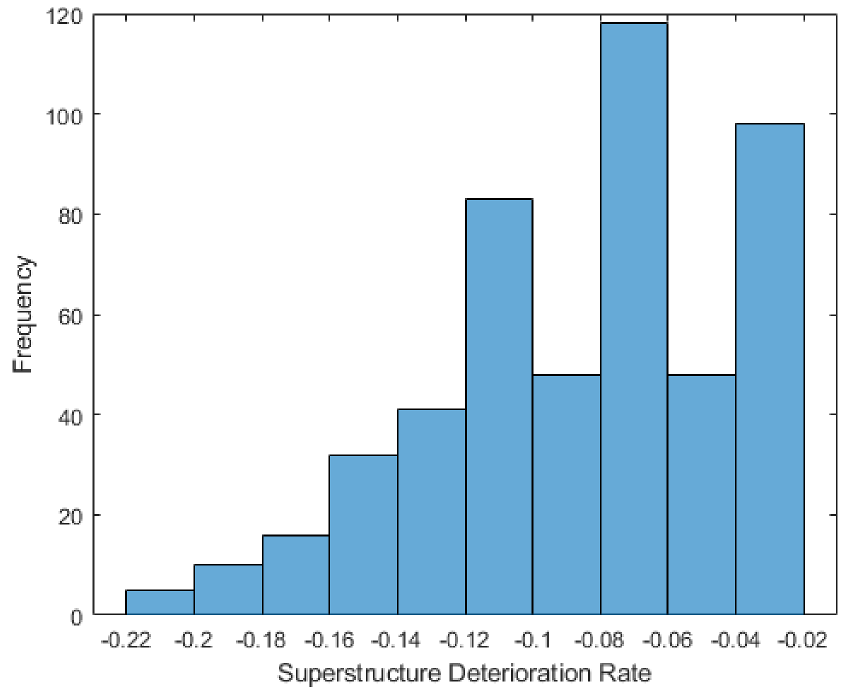


Figure 13: Superstructure deterioration rate frequencies

Correlations between superstructure deterioration and time-independent parameters

When analyzing the time-independent parameters for bridge superstructure, it became clear that no strong correlations exist between the calculated superstructure deterioration rates and the considered parameters. The computed correlation coefficient for each parameter is listed in Table 11 and Table 12. As can be seen, item type of design and/or construction shows the highest correlation coefficient of -0.0769, which is, however, still very low.

Categorical time-independent parameters	Spearman correlation coefficient
Functional Classification	-0.0656
Lanes on Structure	-0.0187
Design Load	0.0220
Type of Service on Bridge	-0.0189
Kind of Material and/or Design	-0.0528
Type of Design and/or Construction	-0.0769
Number of Spans	-0.0434

Table 11: Spearman correlation coefficient for superstructure deterioration rates vs categorical time-independent parameters

Continuous time-independent parameters	Pearson correlation coefficient
Structure Length	0.0035
Length of maximum Span	0.0179
Year Built	0.0337

Table 12: Pearson correlation coefficient for superstructure deterioration rates vs continuous time-independent parameters

The associating graphs for all continuous and categorial time-dependent parameters can be found in Appendix D – Figures for superstructure correlation analysis.

Although no clear correlation could be observed, box plots for the same parameters that were presented for bridge deck in section 4.3.1 are shown for bridge superstructure to compare their results. Figure 14 shows the box plot for lanes on structure versus superstructure deterioration rate. The graph shows similar features to the one for bridge deck. For 1 to 6 lanes on structure, the median deterioration rate is almost equal, for the rest of the categories, the values are differing. The greatest deterioration rates could be found for bridges with 1, 2 and 4 lanes on structure. As mentioned in the previous section, one possible reason for this is the small number of bridges that showed more than 6 lanes on structure, so these bridges are not sufficiently well enough represented to allow any clear statements.

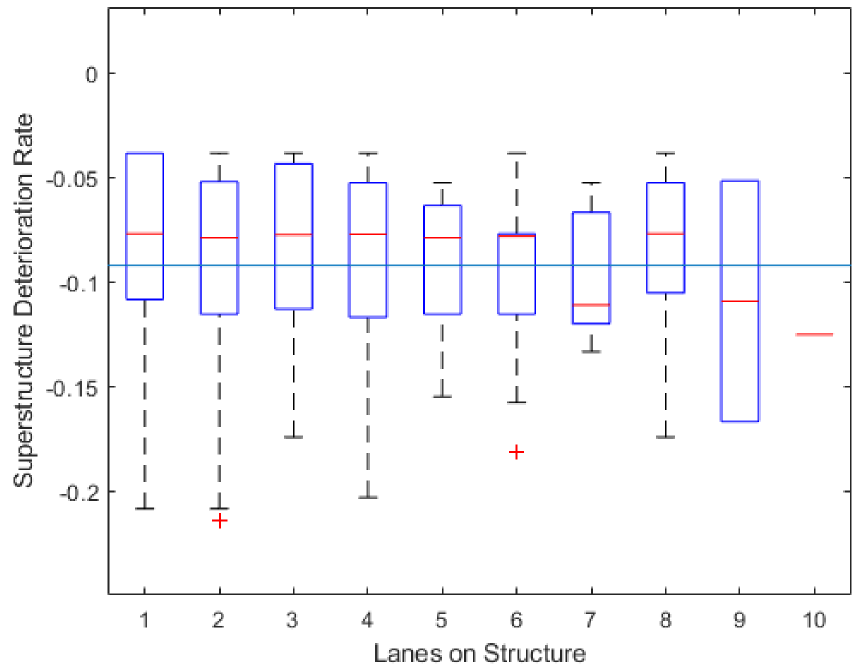


Figure 14: Box plot for superstructure deterioration rate vs. lanes on structure

In Figure 15 the superstructure deterioration rate versus structure kind is depicted. Compared to bridge deck, categories 3 (steel) and 5 (prestressed concrete) show much greater deterioration rates. Bridges of categories 1 (concrete) and 7 (wood or timber) however, show similar values. As for bridge deck, the greatest deterioration rate can be found for wood or timber bridges.

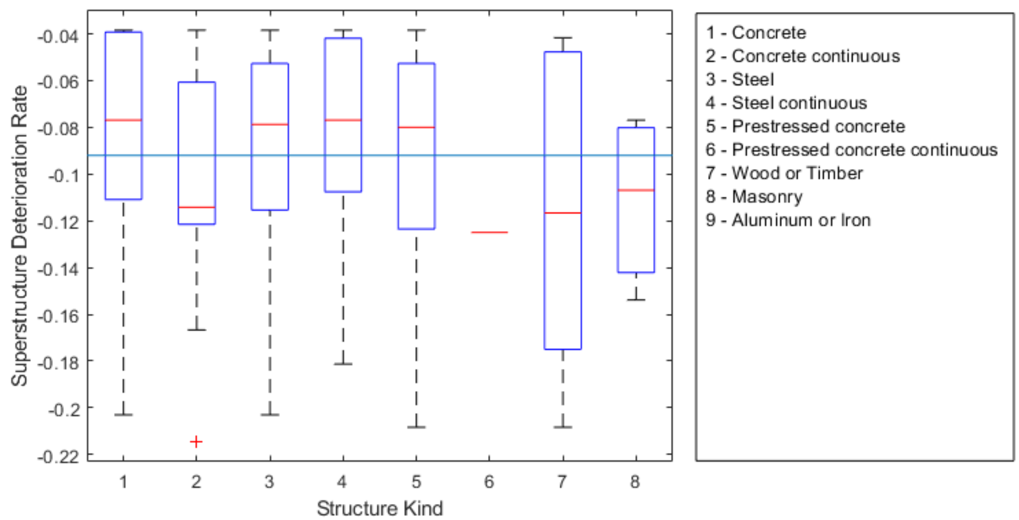


Figure 15: Box plot superstructure deterioration rate vs. structure kind

Correlations between superstructure deterioration and time-dependent parameters

To investigate any correlations between superstructure deterioration and the time-dependent parameters the condition ratings for superstructure were used, as it was done the same way for bridge deck. The computed correlation coefficients are summarized in Table 13 and Table 14. The strongest, but still weak correlation could be found between superstructure and substructure, which is slightly greater than the correlation between superstructure and bridge deck. Notable is that the correlation coefficients for ADT and ADTT are more similar to each other than they were for bridge deck. However, they are both very low and hence indicate that no strong correlation between those parameters and superstructure deterioration exist. Since the computed correlations are not strong at all no graphs are shown at this point. Instead, the graphs can be viewed in Appendix D – Figures for superstructure correlation analysis.

Continuous time-dependent parameters	Pearson correlation coefficient
Average Daily Traffic (ADT)	-0.0500
Average Daily Truck Traffic (ADTT)	-0.0347

Table 13: Pearson correlation coefficient for superstructure deterioration rates vs continuous time-dependent parameters

Categorical time-dependent parameters	Spearman correlation coefficient
Deck Condition Rating	0.4714
Substructure Condition Rating	0.4871

Table 14: Spearman correlation coefficient for superstructure deterioration rates vs categorical time-dependent parameters

4.3.3 Substructure

The frequencies of the deterioration rates for bridge substructure are shown in Figure 16. 128 bridges showed a deterioration between -0.01 and -0.03, which constitute 27.35 % of the considered bridges. After this point, the deterioration rates experienced a sudden increase, but rise very quickly again. In between -0.03 and -0.06 a smaller number of bridges were settled (70 bridges, 14,96 %). After this point, the deterioration rates experienced a sudden decrease. Only 58 bridges (12.39%) showed deterioration rates between -0.03 and -0.05. However, the frequency rises quickly again, with 115 bridges in between deterioration rates of -0.05 and -0.07. From this point on, the frequencies are continuously decreasing. The highest calculated substructure deterioration rate is -0.273, while the average deterioration rate is -0.078, which are very similar values compared to those for bridge deck.

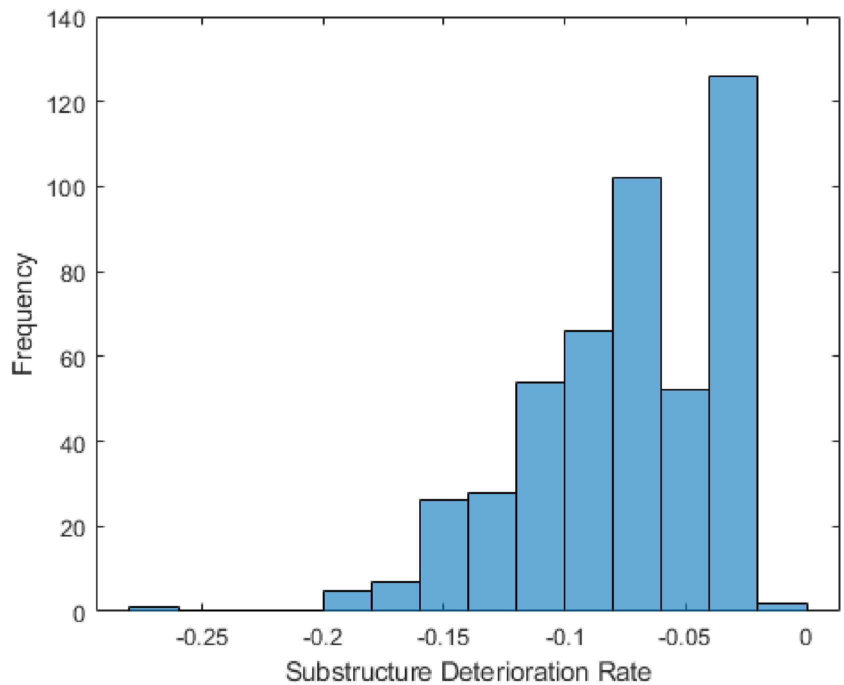


Figure 16: Substructure deterioration rate frequencies

Correlations between substructure deterioration and time-independent parameters

The greatest correlation coefficient between bridge element substructure and all considered time-independent parameters was calculated for item type of service on bridge, which is however not very strong. The results for substructure are not very surprising since the analysis for elements deck and superstructure showed no strong correlations either. All computed correlation coefficients are listed in Table 15 and Table 16. The associating graphs can be found in Appendix E – Figures for substructure correlation analysis.

Categorial time-independent parameters	Spearman correlation coefficient
Functional Classification	0.0368
Lanes on Structure	-0.0094
Design Load	-0.1019
Type of Service on Bridge	0.1090
Kind of Material and/or Design	0.00049
Type of Design and/or Construction	-0.0013
Number of Spans	-0.0827

Table 15: Spearman correlation coefficient for substructure deterioration rates vs categorical time-independent parameters

Continuous time-independent parameters	Pearson correlation coefficient
Structure Length	0.0356
Length of maximum Span	0.0631
Year Built	-0.0624

Table 16: Pearson correlation coefficient for substructure deterioration rates vs continuous time-independent parameters

As in the previous sections, the box plots for parameters number of lanes on structure and structure kind versus substructure deterioration rate are shown to give an insight in the results. The horizontal line in the box plots represents the average deterioration rate of -0.078 for substructure.

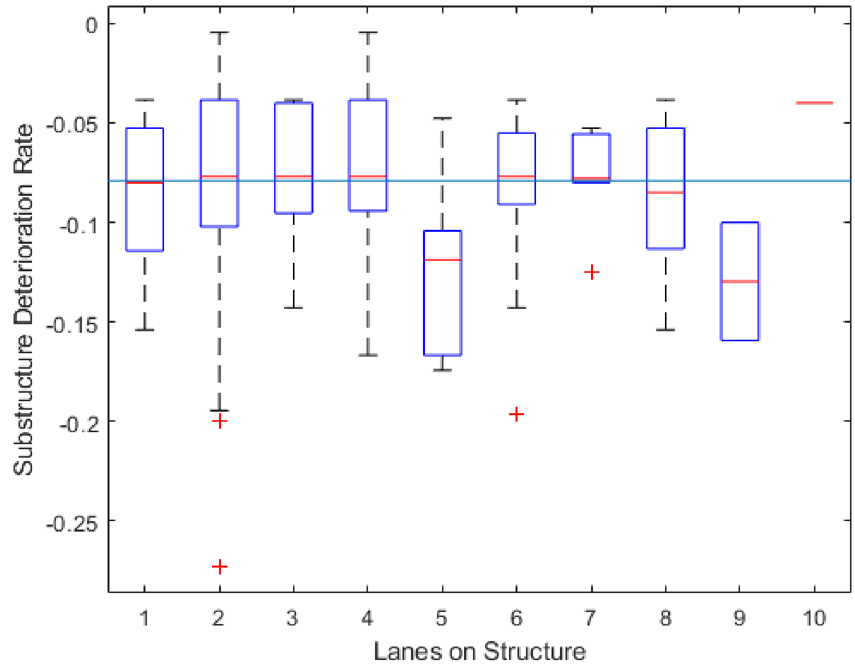


Figure 17: Box plot for substructure deterioration rate vs. lanes on structure

Figure 17 shows the box plot for substructure deterioration rate versus lanes on structure. As for bridge deck and bridge superstructure, bridges constructed with 2 lanes on structure show the highest deterioration rate. Notable is that bridges with 5 lanes on structure show much higher deterioration rates, which is a contrast with the results for the other bridge elements. However, it should be noted that just a small number of bridges with 9 lanes on structure were present.

Figure 18 shows the substructure deterioration rate versus structure kind. Besides structure kind 8 (masonry), all structure kinds show a similar median deterioration rate. The highest deterioration rates could be observed for categories 1 (concrete) and 3 (steel), which is in accordance with the results for bridge deck and superstructure.

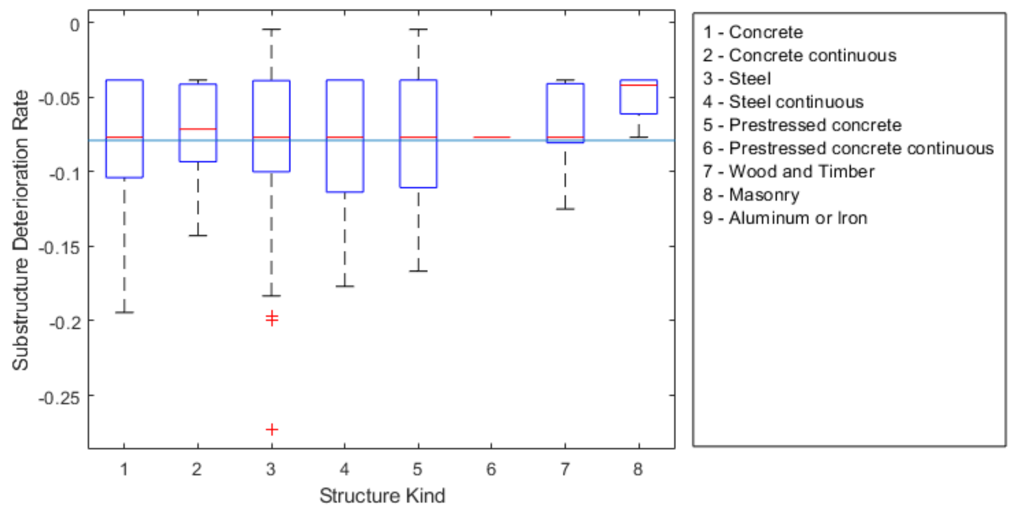


Figure 18: Box plot for substructure deterioration rate vs. structure kind

Correlations between substructure deterioration and time-dependent parameters

For investigations between the substructure deterioration and time-dependent parameters, the same approach as for bridge deck and bridge superstructure was used. Instead of the calculated deterioration rates, the condition ratings were used directly to compute correlations. The results are similar to those for the other bridge elements. The computed correlation coefficients for ADT and ADTT are similar, however very small. The highest correlations could be observed between substructure condition ratings and the superstructure condition ratings, which is a little higher than the correlation between substructure ratings and the deck ratings. All computed correlation coefficients are listed in Table 17 and Table 18. Since no strong correlations could be observed, no graphs for those correlations are shown at this place. The respective graphs can be found in Appendix E – Figures for substructure correlation analysis

Continuous time-dependent parameters	Pearson correlation coefficient
Average Daily Traffic (ADT)	-0.0447
Average Daily Truck Traffic (ADTT)	-0.0339

Table 17: Pearson correlation coefficient for substructure deterioration rates vs continuous time-dependent parameters

Categorical time-dependent parameters	Spearman correlation coefficient
Deck Condition Rating	0.4025
Superstructure Condition Rating	0.4955

Table 18: Spearman correlation coefficient for substructure deterioration rates vs categorical time-dependent parameters

5. BRIDGE DETERIORATION MODEL

According to the American Society of Civil Engineers (ASCE), almost one in four bridges in Rhode Island has been rated structurally deficient in 2017, which makes it the state with the highest rate of structurally deficient bridges in the USA. The problem of deteriorated bridges is therefore nowhere else more critical than in Rhode Island. In this chapter three bridge deterioration models based on the National Bridge Inventory (NBI) database was developed for the state of Rhode Island, which are able to predict the future condition of bridge elements deck, superstructure, and substructure respectively. The deterioration models were designed as Dynamic Bayesian Networks (DBN) since DBNs are able to effectively incorporate system related uncertainties and have proved to be very suitable for modeling deteriorating systems [25]. The design process of the DBN structure is described in section 5.1, while section 5.2 covers the estimation of the model's parameters.

5.1 Model Structure

The subject of this study is the development of three DBNs which describe the relationship between the condition of individual bridge elements and several bridge related parameters. As described in 3.1.1, a BN and hence also a DBN consists of nodes and edges, which represent random variables and conditional dependencies, respectively. Within the developed models, the individual bridge elements and bridge parameters constitute the random variables of the DBNs, while the directed links describe their dependencies. The bridge parameters were selected from the NBI since it provides a useful database containing inventory data, maintenance and inspection data for almost every bridge in the USA. A list of all NBI items along with a detailed description can be found in the *Recording and Coding Guide for the Structure Inventory and Appraisal of the Nation's Bridges* [5]. These items are either time-dependent such as average daily traffic (ADT) and average daily truck traffic (ADTT) or time-independent such as structure number, year built and location. The items that were considered for this study and modeled as nodes in the DBN are listed below in Table 19.

	NBI item	***Item Number***
Time-dependent	Average Daily Traffic (ADT)	#29
	Average Daily Truck Traffic (ADTT)	#109
	Deck Rating	#58
	Superstructure Rating	#59
	Substructure Rating	#60
Time-independent	Lanes on Structure	#28A
	Number of Spans	#45
	Structure Length	#49

Table 19: Considered NBI items for the DBNs

Bridges are usually divided into smaller components such as deck, superstructure, and substructure. The Federal Highway Administration (FHWA) inspects these bridge components individually every year and provides an estimation of their respective condition by means of numerical values, termed condition ratings, as described in 2.1.2. In the course of this study, three DBNs were developed, one for each of the bridge elements in connection with the bridge parameters listed above. Additionally, a variable was included which would account for the influence of maintenance actions.

The DBN describing the relationship between bridge deck and the individual bridge parameters is illustrated in Figure 19.

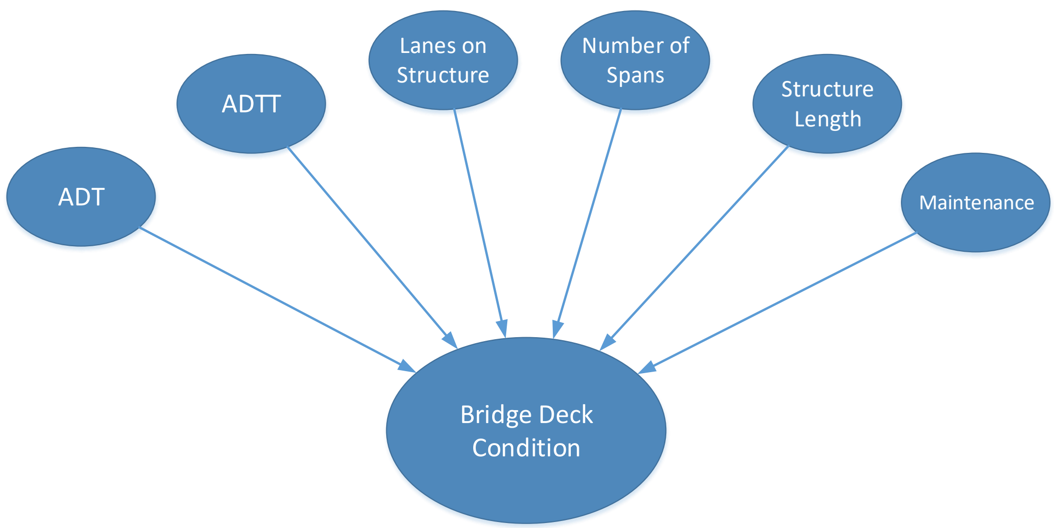


Figure 19: Originally planned DBN

The DBN is decomposed into two hierarchies. In the top hierarchy the variables ADT, ADTT, lanes on structure, number of spans and structure length are linked as parent nodes to variable bridge deck condition, which is the child node and further constitutes the lower hierarchy of the DBN. Originally it was planned to use the NBI items as the model's variables that showed the strongest correlation to bridge deterioration. However, since no clear correlation at all could be observed during the analysis in section 4.3, the selection of the model's variables was based on the findings of previous research in this field. Therefore, it is reasonable to design ADT and ADTT as the parent variable of bridge deck condition since those factors are known to have a great impact on bridge deterioration [24]. Further, NBI items lanes on structure, number of spans and structure were selected. In previous research, an increase in the number of spans in the main unit has been observed to be a contributing factor to a higher deterioration rate. The same can be found to be applicable for the item of structure length since longer bridges are exposed to higher tensile stresses [24]. In an earlier stage of the DBN design, it was originally planned to include several other parameters such as year built, material kind, design load, type of service and deck width in the model, but due to the fact that the number of required conditional probabilities increase exponentially with the number of parent nodes, these parameters were neglected. According to Langseth and Portinale, too many parent variables significantly reduce the computational efficiency of the network [12].

Now having defined the directed acyclic graph (DAG) for the DBN, the next step was to specify the mutually exclusive states of the individual variables. As stated in 2.1.2 the FHWA divides the overall condition of the bridge elements into different 10 ratings, ranging from 0 to 9, where 9 defines the best and 0 the worst condition. Hence it would sound reasonable to define 10 possible states for the bridge element variable. Further, as a first approximation, each parent variable was decided to be assigned with four different states, except for variable maintenance, which was given two states. Now when looking on the conditional probabilities that need to be specified for the bridge element variable, it occurs that in total $10 \times 4^5 \times 2 = 20480$ probabilities would be necessary. Not only would this amount of conditional probabilities lead to a very time-consuming implementation process, but most of all, the available data in the NBI is nowhere near sufficient to provide the estimation of reliable and accurate conditional probabilities since just 578 bridges were taken into consideration. Therefore, a more rough discretization for the individual variables has been chosen by assigning each variable with three possible states, except for variable maintenance. The updated amount of required conditional probabilities is now $3^6 \times 2 = 1458$. It occurs that the necessary amount of conditional probabilities is still very high. A straightforward and commonly applied technique in BN applications to deal with this problem is to introduce auxiliary nodes (intermediate variables).

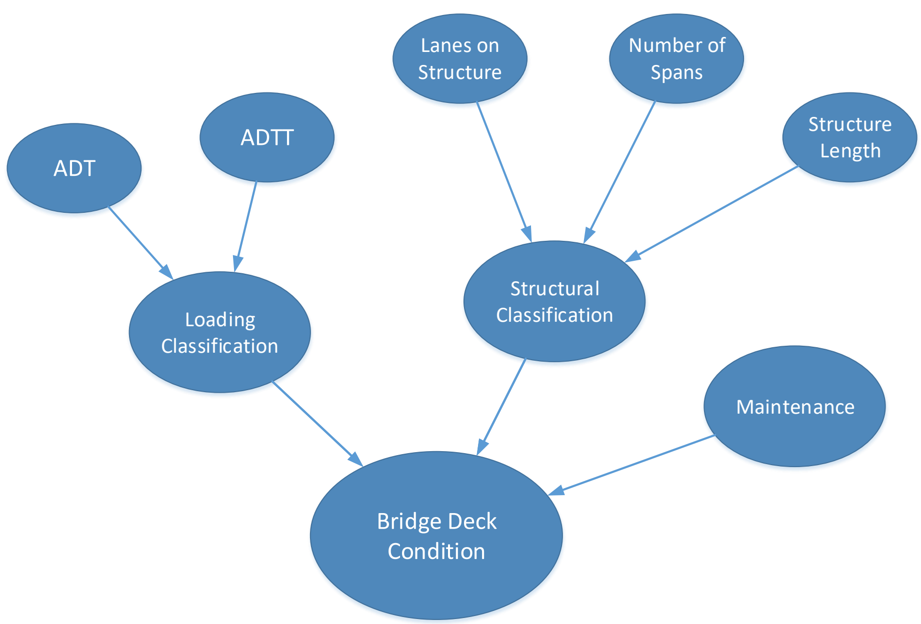


Figure 20: Applied DBN

By means of auxiliary nodes the number of conditional probabilities that need to be specified, can be effectively reduced. By inserting new nodes between the respective bridge element node and its parent nodes, their connection is indirectly enabled. The new DBN with incorporated auxiliary nodes is depicted in Figure 20.

According to Wang, "by means of auxiliary nodes, inference efficiency of the whole network can be improved dramatically" [12]. It should be noted that the auxiliary nodes do not have to have a practical meaning, but indirectly capture the connection between the parent and child variables. In the developed DBN in Figure 20, the auxiliary node termed as loading classification has been set between the node bridge deck condition and the nodes ADT and ADTT, while another auxiliary node termed structural classification was set between the node bridge deck condition and the nodes structure length, number of spans and number of lanes. Each of those auxiliary nodes was defined with 3 different states, which depend on the current state of their respective parent variables. Compared to the original model the bridge element node now has three instead of six parent nodes. Although now also conditional probabilities have to be defined for the auxiliary nodes, the total amount of required conditional probabilities has been considerably reduced to $3^3 + 3^4 + (3^3 \times 2) = 162$.

It should be noted that at this stage, the developed model is just a BN and not yet a DBN. In order to extend the model to a DBN, a time dimension has to be introduced, as described in 3.2. The variables that are affected by this extension, are all time-dependent variables in the model, which are ADT, ADTT, maintenance and the respective bridge element condition variable. These variables can have a different state at every time slice (t_i). The bridge element condition variable is assigned with temporal links at every time slice, which are directed to the corresponding variable in the next consecutive time slice (t_{i+1}). For instance, at time $t_1 = 0$ the variable bridge deck is directly linked to the successive bridge deck variable in the next time-slice at time $t_2 = 1$.

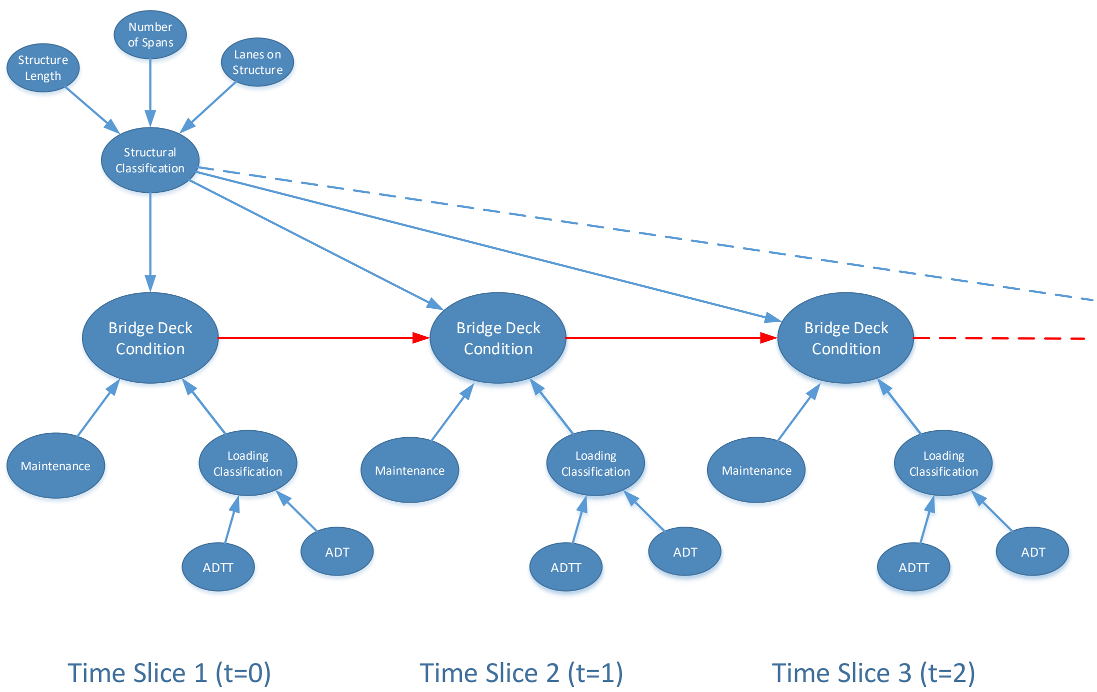


Figure 21: DBN model for bridge deck condition prediction

The operating principle of the completed and later applied DBNs is further illustrated in Figure 21. The remaining time-invariant variables namely structure length, number of spans and number of lanes are static and are hence only specified one-time in the initial time-slice. They are connected to the corresponding variables of each time-slice.

It has to be mentioned that with the extension to a DBN the number of required conditional probabilities increases again since the variable bridge deck condition is now also dependent on its state in the preceding time slice. The final number of required conditional probabilities for each DBN is hence calculated to $3^3 + 3^4 + (3^4 \times 2) = 270$. For the time interval, one year has been chosen since the FHWA provides inspection records annually.

5.2 Parameter Estimation

In this section, the determining of the DBNs parameters is described in detail. The parameters of the DBN are the marginal and conditional probabilities, which are based on several items of the NBI database. The computation of these probabilities is made using the filtered data sets from section 4.1. In section 5.2.1 and 5.2.2, the calculation of the conditional and marginal probabilities using the filtered datasets is described.

5.2.1 Calculation of Conditional Probabilities

The conditional probabilities are the quantitative part of a BN and can be interpreted as a representation of the dependence relationship between the model‘s variables. Conditional probabilities need to be specified for each child variable. Hence, for the described DBN in section 5.1, conditional probabilities need to be determined for nodes loading classification, structural classification, and the respective bridge element condition node. The conditional probabilities for each child node are stored in conditional probability tables (CPT).

As briefly mentioned in 5.1, each variable of the DBNs except for variable maintenance was given three mutually exclusive states. For the variables lanes on structure, structure length, ADT, and ADTT the three states were defined as “low“, “moderate“ and “high“, as it was for the intermediate nodes structural classification and loading classification. For the condition ratings, the three states were defined as “poor“, “satisfactory“ and “good“. A state of poor was given to a bridge if the condition rating in the corresponding year was between 0 and 4, a state of satisfactory was given for ratings of 5 and 6, and a state of good was given for ratings between 7 and 9. The classification of the states for the bridge element condition variable is summarized in Table 20.

Condition Rating	**State of the bridge elment variable**
9	
8	Good
7	
6	Satisfactory
5	
4	
3	
2	Poor
1	
0	

Table 20: Bridge element variable classification

For the variables lanes on structure, number of spans and structure length, the classification in which state a variable is, was based on the analysis of the NBI items for Rhode Island. The classification was made in such a way that the three different states for each variable are more or less equally distributed, if possible. The classification for variables lanes on structure, number of spans and structure length is given in Table 21.

Variable	**State**		
	Low	Moderate	High
Lanes on Structure	1	2	>2
Number of Spans	1	2	>2
Structure Length	0-20 m	20-50 m	> 50 m

Table 21: Time-independent variable classification

When analyzing the filtered NBI datasets, it has been observed that for item lanes on structure 9% of all bridges in Rhode Island were built with 1 lane, 64% with 2 lanes and 27% with 3 or more lanes. The item number of spans was distributed with 55% for 1 span, 19% for 2 spans and 26% for 3 or more spans. The same approach was taken for variables ADT and ADTT. Based on the distribution of the items in the filtered dataset, ADT and ADTT were classified as shown in Table 22, where the number for the respective variables represent the annual number of vehicles crossing the bridge.

Variable	State		
	Low	Moderate	High
ADT	≤ 5000	5000-15000	>15000
ADTT	≤ 500	500-1500	>1500

Table 22: Time-dependent variable classification

The intermediate variables structural classification and loading classification were added to significantly reduce the required number of conditional probabilities, as described in 5.1. These intermediate nodes do not have a practical meaning, but indirectly enable the connection between the parent variables and bridge element condition variable. As mentioned above, for these variables also the three different states low, moderate and high were defined. In which state these variables are, depends on the current state of its respective parent variables. For this purpose, the three states low, moderate and high of each of the parent variable were assigned with a numerical value. A value of 1 was assigned for the state of low, a value of 2 was assigned for moderate, and a value of 3 was assigned for state high. These values of all parent variables of one common node were then summed, and based on this sum the intermediate child node was classified. For variable structural classification, a state of low was given if the sum of all values of its parent variables states was smaller than 5. For a state of moderate the sum had to be between 5 and 7, and for state high the sum had to be greater or equal to 8. For instance, if a bridge was built with 2 spans, 1 lane and had a structure length of 52 meters, the sum of values would be 2 + 1 + 2 = 5, which would result in a state of moderate for variable structural classification. The classification for the intermediate nodes is summarized in Table 23.

Variable	State	Sum of values given for the parent variables
Structural Classification	Low	<5
	Moderate	5-7
	High	>7
Loading Classification	Low	<4
	Moderate	=4
	High	>4

Table 23: Classification for variables Structural Classification and Loading Classification

The same approach was taken for the intermediate variable loading classification, which depends on variables ADT and ADTT. In this case, as node loading classification has only 2 parent variables, a state of low was given for a sum of values smaller than 4, a state of moderate was given for a sum of values was equal to 4, and the state of high was given for a sum of values greater than 4. This way of classifyingresults in the following CPT for node Loading Classification, as shown in Figure 22.

Loading Classification

ADT	Low			Moderate			High		
ADTT	Low	Moderate	High	Low	Moderate	High	Low	Moderate	High
Low	1	1		1					
Moderate			1		1		1		
High						1		1	1

Figure 22: CPT - Loading Classification

For each bridge element, two different CPTs need to be specified. One for the initial time slice, in which the bridge element condition does not depend on a previous element condition since no previous condition is present, and the CPTs for all other time slices, where the current bridge element condition depends on the respective preceding condition. The conditional probabilities for the bridge element variables were computed using the Maximum Likelikhood Estimation (MLE) method as described in 3.3.1. Its application on the developed DBNs is further described by means of a sample calculation. Consider the following table for six exemplary bridges, as shown in Figure 23.

SC = Structrual Classification LC = Loading Classification DC = Deck Condition Rating

Bridge ID	SC	1992		1993		1994		1995		1996		1997		1998		1999	
		LC	DC	LC	DC	LC	DC	LC	DC	LC	DC	LC	DC	LC	DC	LC	DC
60	1	3	7	3	7	3	6	3	6	3	6	3	6	2	6	2	6
110	2	2	7	2	6	2	6	2	6	2	6	2	6	2	6	2	6
150	1	3	7	3	7	3	5	3	5	3	5	3	5	3	5	3	5
170	2	2	8	2	8	2	8	2	8	2	7	2	7	2	7	2	6
200	1	2	7	2	7	2	7	2	7	2	6	2	7	2	7	2	7
220	2	2	7	2	6	2	6	2	6	2	6	2	6	2	6	2	6

Figure 23: Example for computing the CPT for bridge deck

For example, the probability for the bridge deck to be in state satisfactory, given that its parent variables structural classification and loading classification are in state moderate, and that the deck condition in the year before was in a state of good, would be calculated as follows:

$$P(DC = s|SC = m, LC = m, DC_{-1} = g) = \frac{n(s,m,m,g)}{n(g,m,m,g) + n(s,m,m,g)}$$

$$= \frac{3}{6+3} = \frac{1}{3}$$

With the following abbreviations:

DC = Deck Condition	s = satisfactory
SC = Structural Classification	m = moderate
LC = Loading Classification	g = good

Where $n(s,m,m,g)$ represents the count of the frequency for the case that variable deck condition is in a state of satisfactory, structural classification and loading classification are in a state of moderate, and the deck condition of the previous year was in a good condition.

An extract of the CPT for the variable bridge deck is shown in Figure 24. As can be seen, the conditional probability of a bridge to be poor given that its condition in the previous year was poor, is always 1, or in other words 100%, except when a maintenance action was applied, in this case, the bridge element was reset to a state of good. Since the aim of this study was to simulate the normal operating deterioration process of bridges, a bridge should not be able to improve its condition, without maintenance actions. Therefore, when calculating the conditional probabilities, transitions from worse to better conditions were neglected.

The CPTs for each of the three DBNs can be found in Appendix G – Conditional probability tables.

Structural	Poor											
Loading	Poor						Satisfactory					
Previous Condition	Poor		Satisfactory		Good		Poor		Satisfactory		Good	
Maintenance	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Poor	1	0	0.018215	0	0.001374	0	1	0	0.006263	0	0	0
Satisfactory	0	0	0.981785	0	0.048077	0	0	0	0.993737	0	0.035897	0
Good	0	1	0	1	0.950549	1	0	1	0	1	0.964103	1

Figure 24: Extract of the CPT - Deck Condition

5.2.2 Calculation of Marginal Probabilities

For all root nodes of the DBNs, marginal probabilities needed to be determined. The marginal probabilities are simply calculated as the frequency of a variable to be in a certain state, divided by the sum of the frequencies of every possible state of that variable. The marginal probabilities for variables lanes on structure, number of spans, structure length, ADT, and ADTT are listed in Appendix F – Marginal probabilities.

5.3 Results

5.3.1 Bridge Element Condition Prediction

After defining the structure of the DBNs and the accomplished calculation of the CPTs, the developed deterioration models for bridge elements deck, superstructure, and substructure were then used to predict the future condition of each individual bridge element for different input parameters. The predictions are performed using the software GeNIe, which runs the clustering algorithm to perform inference. The GeNIe Modeler is available free of charge for academic research and teaching use from BayesFusion, LLC, http://www.bayesfusion.com/. The by GeNIe calculated probabilities were then imported into Excel and plotted in graphs over time.

Deck

The deterioration models can be used to calculate the future bridge element condition probabilities for different scenarios. These scenarios vary depending on the input parameters for the parent variables of the respective bridge element variable. However, predictions can also be performed without assigning any variable in a fixed state. In this case, the predictions are calculated using the probability distributions of the models CPTs and marginal probabilities tables only. For instance, Figure 25 shows the prediction for element bridge deck for 50 years, where no parameters have been specified.

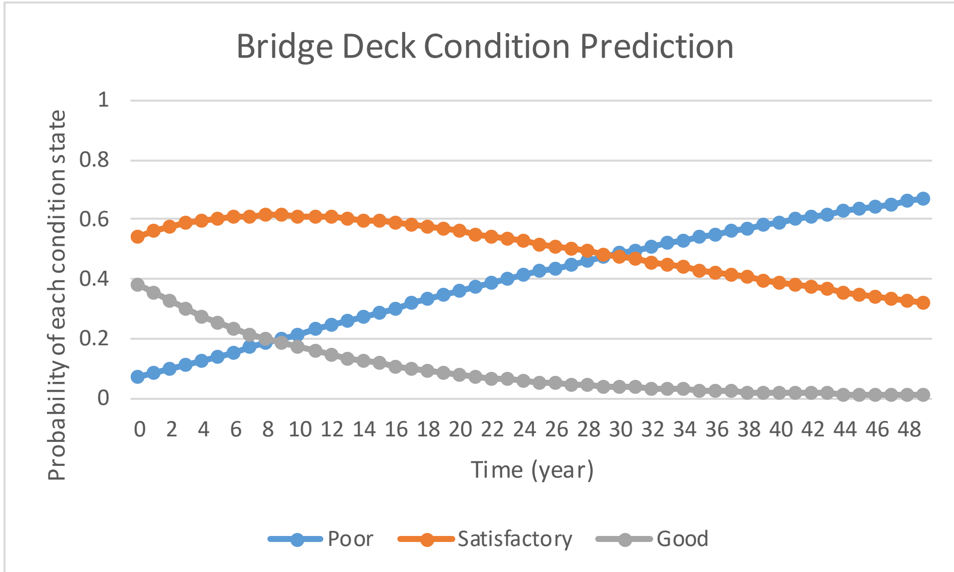


Figure 25: Time series for bridge deck over the next 50 years without specified parameters

The statements that can be derived from these predictions are however very general and may not be very meaningful and expedient. Usually, predictions based on several assumptions for the input variables are of more interest. Figure 26 shows the prediction for the next 50 years with the bridge deck assumed to be in an initial state of good. Accordingly, as can be seen, the probability for bridge deck to be in a good state starts with 100%. From this point on, the curve for the state of good strives to zero. The curve for the state of satisfactory reaches its peak at year 21 with 59.19%. The curve for the state of poor is almost a straight line going up. At year 50, the bridge will most likely be in a state of poor, with a probability of 56.75%, while the chance that the bridge will be in a state of good is with a probability of 2.73% very unlikely.

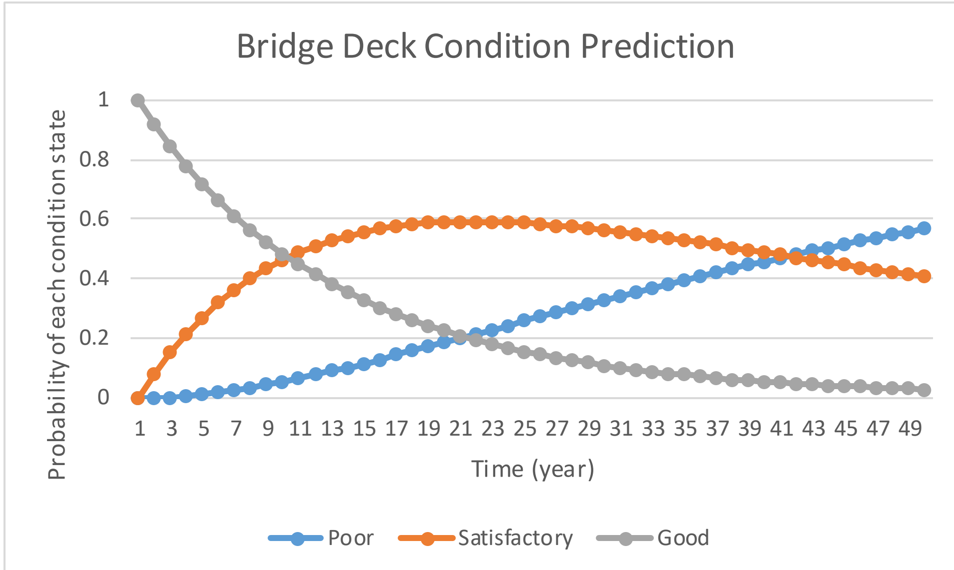


Figure 26: Time series for bridge deck over the next 50 years under the assumption of an initial state of good

Two further scenarios are conducted, which involve assumptions for the initial bridge deck condition and the two intermediate variables loading classification and structural classification. In the first scenario, the bridge is assumed to be in a good initial state, while variable structural classification and variable loading classification are assumed to be in a state of high for all 50 years. Furthermore, a perfect maintenance action at year 25 is simulated, which renews the bridge deck and brings it back into a state of good. The evolution curve of the bridge deck is illustrated in Figure 27.

In the second scenario, the same assumptions as in the first scenario were made, except that variables structural classification and loading classification were assumed to be in a state of low during all 50 years. The associated evolution curve is shown in Figure 28.

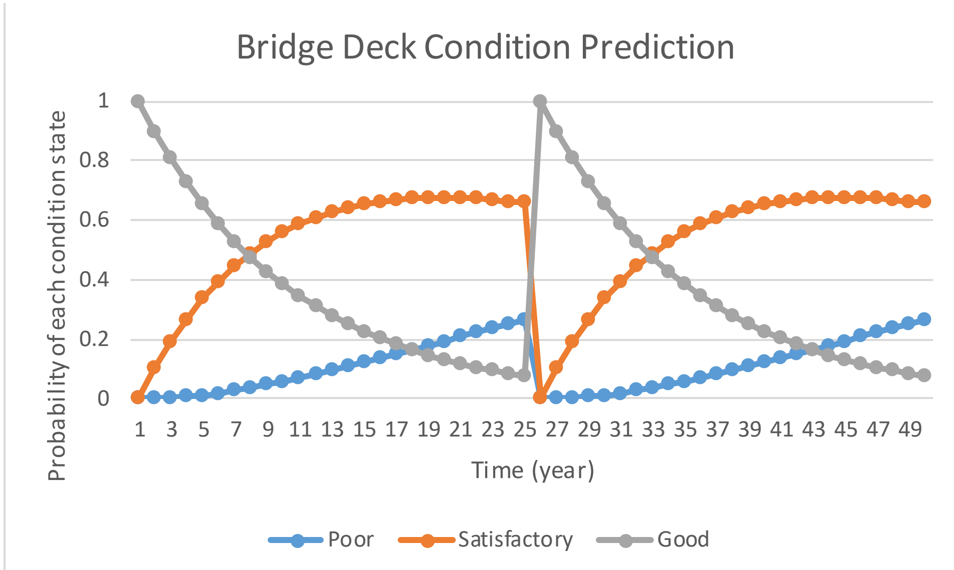


Figure 27: Time series for bridge deck over the next 50 years under the assumption of an initial state of good, structural classification and loading classification as high, and a perfect maintenance action at year 25

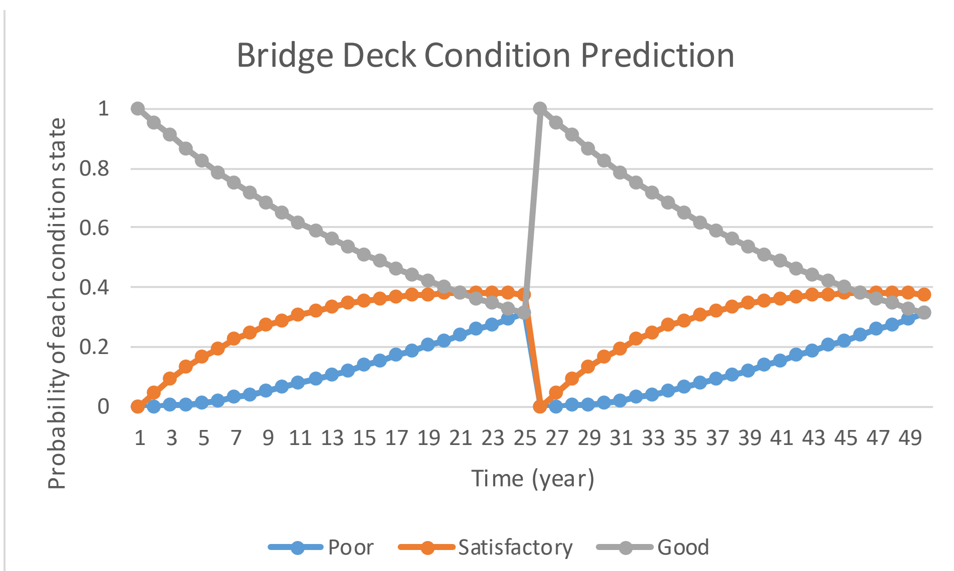


Figure 28: Time series for bridge deck over the next 50 years under the assumption of an initial state of good, structural classification and loading classification as low, and a perfect maintenance action at year 25

The biggest difference between those two diagrams clearly constitutes the course of the curves for the state of satisfactory. In the first scenario, the bridge is much more likely to be in a state of satisfactory. At year 19 the curve reaches its maximum with 67.45%. The curve in Figure 28, in comparison, has its maximum at year 21 with just 37.99%. It can further be observed that the evolution curve for the state of good declines much faster in the first scenario, while the curves for the state of poor show a similar course in both scenarios. Further notable is, that in the second scenario the probabilities for each state in year 25 and year 50, are almost equally distributed.

Superstructure

For bridge element superstructure the same predictions were made as for bridge deck. Figure 29 illustrates the prediction for bridge superstructure over the next 50 years, under the assumption of an initial state of good. The predictions for superstructure showed a similar character than those for bridge deck. However, the curve for the state of satisfactory in Figure 29 reaches its maximum earlier and also declines much faster than the respective curve in Figure 28. Furthermore, the curve of the state of poor for bridge superstructure rises with a greater slope. Overall, it can be concluded that bridge element superstructure deteriorates faster than bridge element deck.

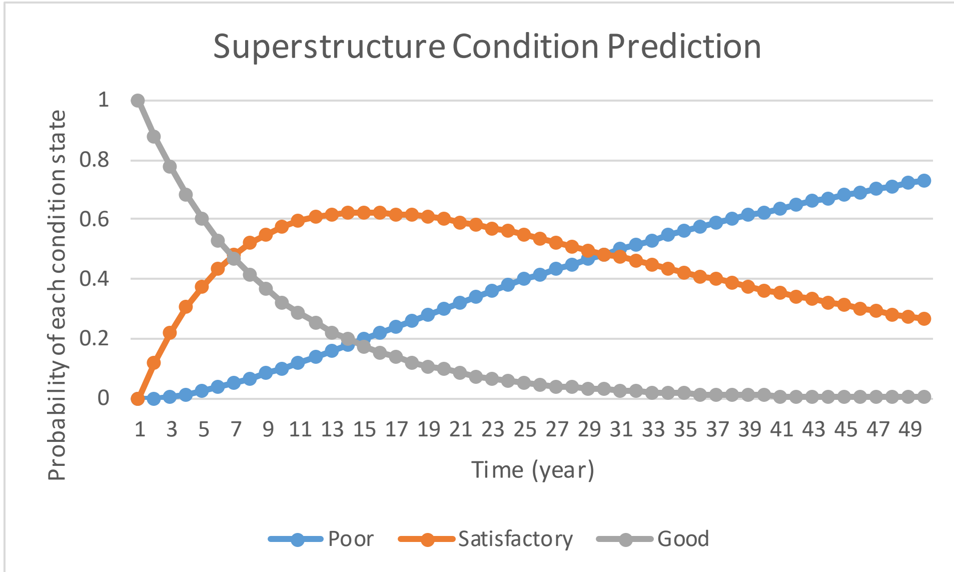


Figure 29: Time series for bridge superstructure over the next 50 years under the assumption of an initial state of good

The graphs involving assumptions for variables loading- and structural classification for bridge superstructure can be found in Appendix H – Figures for bridge element condition prediction. Since they showed a similar character compared to those for bridge deck, they are not shown at this place.

Substructure

Also for bridge element substructure, the same predictions were made as for bridge deck. The prediction diagram for the condition of bridge element substructure over the next 50 years, under the assumption of an initial state of good, is depicted in Figure 30.

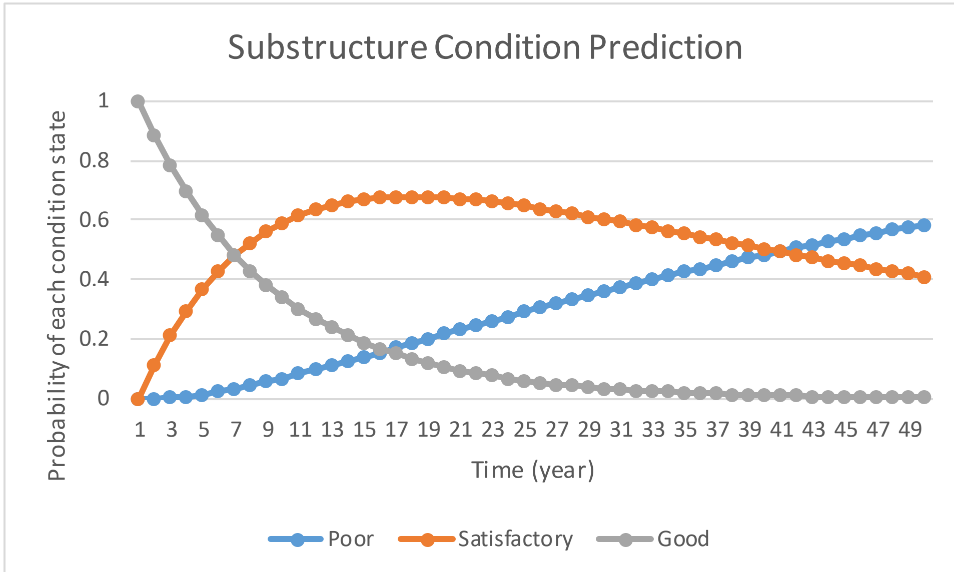


Figure 30:Time series for bridge substructure over the next 50 years under the assumption of an initial state of good

The diagram for bridge substructures shows similarities to both of the previous elements, deck, and superstructure. Until year 20 the curves of all states are very similar to those for bridge superstructure. However, from this point on the curves start to run more similar to those for bridge deck. At the end of the diagrams in year 50, the probabilities of both elements are almost equal.

Also, in this case, the graphs involving assumptions for variables loading- and structural classification for bridge superstructure did not provide any more interesting information and are hence only placed in Appendix H – Figures for bridge element condition prediction.

5.3.2 Sensitivity Analysis

By means of a sensitivity analysis, the strength of impact each bridge parameter (i.e. lanes on structure, number of spans, structure length, ADT, and ADTT) has on each of the three bridge elements was investigated respectively. This was done performing „what-if" scenarios, where the effects of evidence for individual variables in the DBN on the respective bridge element condition variable was examined. For all three DBN models, each bridge parameter was one by one (in turn) assigned with a state of low, while all other remaining parameters kept their original probability distributions. The effect of the evidence was then determined by calculating the difference between the resulting probability distribution of the bridge element condition variable and it's probability distribution where no evidence is present. This was done for all three possible states of the bridge parameters: low, moderate and high. The effects of evidence from all three states were then summed for each bridge parameter. To calculate the impact each bridge parameter has on the bridge element condition, the summed effects of each individual bridge parameter were then normalized over the total sum (i.e. Sum of all effects in bridge element condition from each bridge parameter with evidence for each state).

Deck

From Figure 31 it can be observed that the parameters lanes on structure, number of spans and structure length have overall the greatest impact on bridge deck condition, while ADT and ADTT show a clearly lower influence.

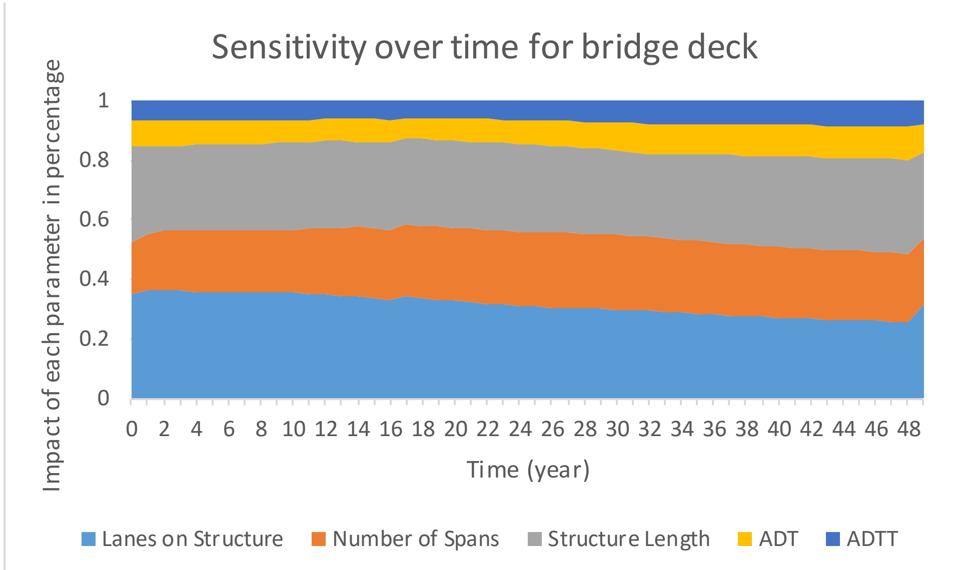


Figure 31: Area chart for the sensitivity of bridge deck for all DBN variables for 50 years

Also, it can be seen that the impact of each parameter stays more or less the same over time and does not significantly change. These results are in a contrast with prior expectations since ADT and ADTT are the only external parameters that really contribute to the deterioration of bridges, and are also known to have a great impact on bridge deterioration [24].

Superstructure

The sensitivity analysis for bridge element superstructure showed significant differences compared to the one for bridge deck. As can be seen in Figure 32 all parameters have overall a more or less equally strong influence on the bridge superstructure. However, unlike in the sensitivity analysis for bridge deck, the impact of each parameter shows considerable changes over the time period of 50 years.

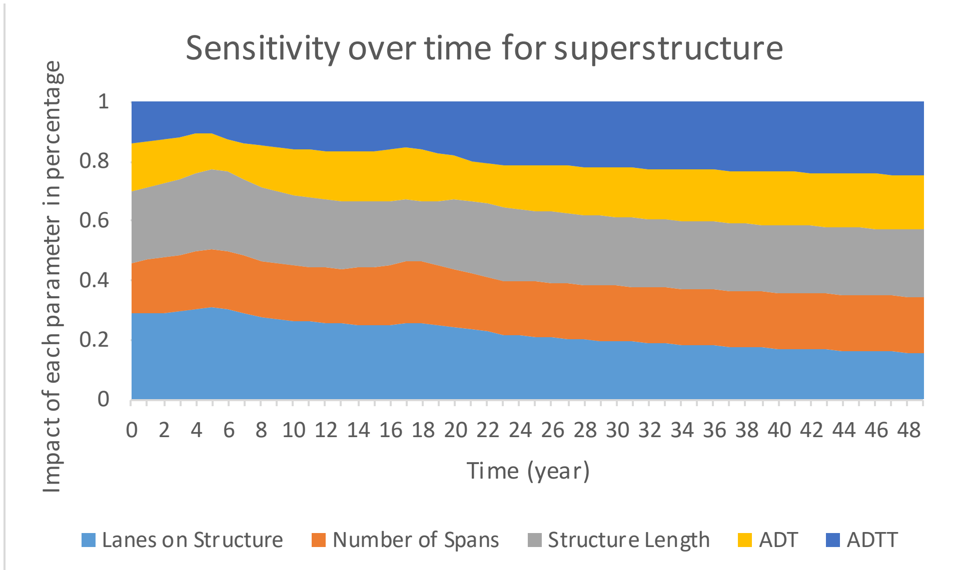


Figure 32: Area chart for the sensitivity of bridge superstructure for all DBN variables for 50 years

While for variables ADT and ADTT the impact clearly increases with time, the impact for lanes on structure decreases of about 13%. Furthermore, around the years 5 and 17, the impact of each parameter seems to experience a sudden switch in direction. A reason for these odd switches could not be found.

Substructure

The results of the sensitivity analysis for bridge substructure are more similar to those for bridge deck than those for bridge superstructure. As for bridge deck, the impacts of parameters ADT and ADTT are the lowest of all parameters, as can be seen in Figure 33. However, the impact of both parameters is much greater compared to those for bridge deck. Parameter lanes on structure show the greatest impact, which also the case for the other bridge elements.

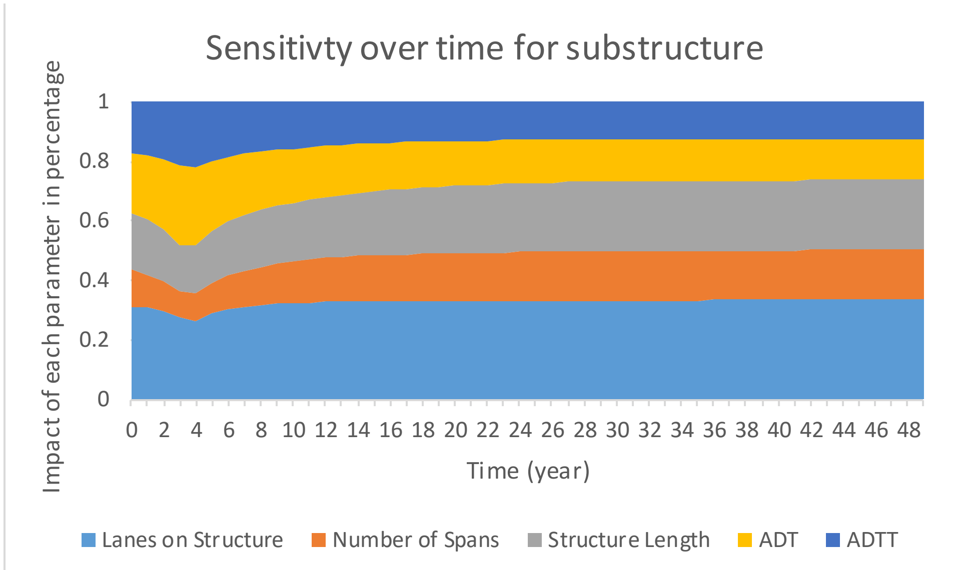


Figure 33: Area chart for the sensitivity of bridge substructure for all DBN variables for 50 years

When observing the diagram in Figure 33, it is striking that around year 4 all parameters seem to experience a sudden switch in direction, similar to the one for bridge substructure. Especially parameters lanes on structure, structure length, and ADT are affected by this. After this sudden change, however, the respective curves drift in a quite linear course.

6. CONCLUSION

6.1 Summary

The objective of this study was to develop three deterioration models, each for one of the bridge elements deck, superstructure, and substructure. The aim was to develop a prediction model based on Dynamic Bayesian Networks (DBN), that is being able to forecast the future condition of major bridge elements. A further aim was to use the National Bridge Inventory (NBI) database to investigate the impact of several bridge related parameters on bridge deterioration in Rhode Island.

When studying possible methods for deriving the DBN parameters, it quickly became clear that statistical data would constitute the basis of the models, since the only other possible option of expert elicitation would exceed the scope of this study. As the source for statistical data, the National Bridge Inventory (NBI) was chosen, which provides an extensive variety of information for USA's bridges, including information regarding design, construction, and maintenance. Chapter 3 of this thesis gives an introduction to Bayesian theory and describes methods to estimate the conditional probability tables (CPT), which constitute the essence of the DBNs. For this purpose, the Maximum Likelihood Estimation (MLE) was chosen, which can be easily applied and operates solely with statistical data. Before the deterioration models were developed, the NBI datasets were filtered in order to sort out inconsistent and unusable data to ultimately achieve reliable results in the later applied deterioration models. Furthermore, the condition ratings of the NBI were used to compute deterioration rates for each bridge element and analyze any possible correlations to several selected NBI items, which constitute either bridge design parameters or loading parameters. In the first part of Chapter 5, the framework of the developed DBNs is described in detail, as is the development of the CPTs using the MLE. In the second part of Chapter 5, the developed DBNs were used to perform several predictions for each bridge element condition for 50 years with varying input parameters. In the course of this, the updating ability of the DBNs was demonstrated by simulating a perfect maintenance action within the considered time period. Lastly, the impact of the model's variables on the individual bridge elements condition was investigated by means of sensitivity analyses.

6.2 Results

In the course NBI data analyzing process, the obtained datasets from the NBI had to run through several filters. About 30% of the data had to be disregarded because of missing and/or incredible data entries. As described in 4.1, for a great number of bridges the condition ratings showed an unusual development, such as ratings that went up and down by one or two ratings, which does not agree with the normal execution of maintenance actions. These slight variations in the condition ratings might derive from subjectivity of different inspectors. Also, other parameters such as number of spans and lanes on structure showed inconsistencies within the datasets. Due to these inconsistencies, the developed deterioration models might be affected in their credibility.

During the correlation analyses between the computed deterioration rates and the considered NBI items, no strong correlations could be observed. This fact further raised concerns about the accuracy of the NBI database.

In the first part of Chapter 5, the developed DBNs were used to predict the future condition for each bridge element for 50 years. Within these predictions, several different assumptions were made to examine their effects on the predicted bridge element conditions. Overall it could be observed that bridge element superstructure deteriorates faster than bridge element deck and substructure. For all bridge elements, the evolution curves of each state showed strong increases or decrease approximately to the first 20 years, after that the curves developed a linear progression. Furthermore, several predictions were made that involved assumptions regarding the variables structural classification and loading classification, as well as a simulation of a perfect maintenance action at year 25. The ability to make assumptions for several bridge parameters within the model allows making predictions for specific bridge groups with similar characteristics.

The second part of Chapter 5 comprises a sensitivity analysis of each bridge element on several in the DBNs incorporated bridge parameters. When evaluating the results of the sensitivity analyses, it became apparent that the diagrams that were derived from the analyses produced contradicting results to some extent, since the different variables partly showed strongly different impacts on the individual bridge elements. A possible reason for this might be the impaired credibility in the used data.

6.3 Future Work

The goal of this study was to develop a deterioration model which is representative of the state of Rhode Island. The heart of the developed deterioration models is the CPTs, which were computed using NBI data of Rhode Islands bridges. At an early stage of the DBNs design process, it was originally planned to include several other parameters such as design load, kind of material and structure type in the models, but due to the limited available data, this first design had to be discarded. A possible way to deal with this problem would be to include the bridge data from other states, which would raise the number of available bridge data significantly. However, a drawback would be that in this case, the deterioration models would not be as representative for the state of Rhode Island anymore.

Another limitation was the presence of errors and inconsistencies in the obtained datasets, which ultimately affected the accuracy of the developed deterioration models. Instead of obtaining bridge data from the NBI, original inspection records could directly be requested from the Rhode Island Department of Transportation (RIDOT), which might give access to more detailed bridge data that has not been submitted to the Federal Highway Administration (FHWA).

Alternatively, the CPTs could be directly estimated by means of expert elicitation as described in section 3.3.2. This way the credibility and accuracy of the deterioration models would be improved since the models would not have to rely on statistical data anymore.

Appendix A - List of approved bridge IDs after filtering

60, 110, 150, 170, 200, 220, 230, 250, 260, 270, 280, 300, 320, 350, 370, 410, 450, 460, 490, 500, 540, 550, 560, 580, 610, 640, 650, 710, 770, 780, 840, 930, 950, 960, 1010, 1070, 1120, 1170, 1180, 1210, 1260, 1310, 1390, 1400, 1440, 1450, 1490, 1500, 1510, 1550, 1630, 1640, 1780, 1790, 1810, 1820, 1850, 1930, 1940, 1970, 1990, 2010, 2040, 2130, 2220, 2240, 2430, 2480, 2490, 2560, 2570, 2600, 2610, 2670, 2700, 2740, 2760, 2762, 2780, 2840, 2860, 2870, 2920, 2940, 2950, 2960, 2990, 3010, 3020, 3070, 3080, 3100, 3170, 3230, 3260, 3270, 3340, 3350, 3370, 3400, 3440, 3450, 3470, 3480, 3500, 3502, 3540, 3550, 3560, 3570, 3630, 3650, 3680, 3690, 3692, 3700, 3710, 3720, 3750, 3760, 3770, 3820, 3830, 3890, 3910, 3950, 3960, 3970, 4000, 4010, 4020, 4030, 4040, 4050, 4060, 4070, 4080, 4100, 4110, 4120, 4130, 4140, 4150, 4160, 4170, 4180, 4190, 4210, 4220, 4230, 4250, 4270, 4280, 4290, 4300, 4320, 4330, 4400, 4420, 4430, 4450, 4460, 4470, 4480, 4490, 4510, 4520, 4540, 4550, 4560, 4570, 4580, 4590, 4600, 4650, 4660, 4670, 4680, 4690, 4710, 4720, 4770, 4790, 4800, 4810, 4830, 4840, 4842, 4850, 4852, 4860, 4862, 4870, 4880, 4890, 4900, 4910, 4930, 4940, 4950, 4990, 5000, 5010, 5030, 5050, 5060, 5110, 5140, 5150, 5170, 5180, 5190, 5200, 5220, 5230, 5240, 5250, 5260, 5270, 5280, 5290, 5300, 5310, 5320, 5330, 5340, 5350, 5360, 5370, 5390, 5420, 5440, 5450, 5460, 5470, 5480, 5490, 5510, 5520, 5522, 5530, 5540, 5550, 5560, 5570, 5580, 5590, 5600, 5610, 5612, 5620, 5622, 5630, 5632, 5650, 5660, 5670, 5680, 5690, 5692, 5700, 5710, 5720, 5730, 5740, 5750, 5760, 5770, 5780, 5790, 5810, 5820, 5830, 5840, 5850, 5860, 5862, 5880, 5882, 5890, 5900, 5910, 5912, 5920, 5922, 5930, 5940, 5950, 5960, 5970, 6000, 6020, 6040, 6050, 6060, 6070, 6090, 6110, 6112, 6160, 6180, 6190, 6200, 6210, 6220, 6230, 6240, 6250, 6260, 6270, 6280, 6290, 6320, 6330, 6340, 6350, 6360, 6370, 6380, 6390, 6420, 6422, 6440, 6450, 6452, 6460, 6462, 6470, 6490, 6492, 6500, 6502, 6510, 6520, 6530, 6550, 6560, 6570, 6580, 6590, 6600, 6610, 6620, 6630, 6640, 6650, 6660, 6670, 6680, 6700, 6720, 6730, 6740, 6750, 6760, 6770, 6780, 6800, 6810, 6820, 6830, 6840, 6850, 6860, 6880, 6890, 6910, 6920, 6970, 6990, 7000, 7010, 7020, 7030, 7040, 7050, 7060, 7070, 7080, 7090, 7100, 7120, 7130, 7140, 7190, 7200, 7210, 7212, 7220, 7222, 7230, 7240, 7260, 7270, 7272, 7280, 7282, 7290, 7292, 7300, 7302, 7310, 7320, 7340, 7342, 7350, 7352, 7360, 7362, 7370, 7372, 7400, 7402, 7410, 7420, 7422, 7430, 7432, 7450, 7452, 7460, 7462, 7470, 7480, 7482, 7490, 7500, 7502, 7510, 7520, 7522, 7530, 7532, 7540, 7550, 7552, 7570, 7572, 7580, 7600, 7610, 7630, 7650, 7660, 7670, 7680, 7700, 7710, 7720, 7730, 7740, 7750, 7770, 7800, 7810, 7820, 7830, 7850, 7870, 7880, 7890, 7900, 7920, 7960, 7970, 7980, 8000, 8200, 8210, 8220, 8240, 8270, 8310, 8340, 8360, 8400, 8410, 8412, 8480, 8490, 8500, 8510, 8530, 8540, 8550, 8560, 8580, 8590, 8640, 8650, 8660, 8670, 8672, 8680, 8700, 8720, 8740, 8760, 8780, 8790, 8800, 8820, 8830, 8840, 8870, 8880, 8890, 8900, 8930, 8940, 8950, 8960, 8980, 8990, 9000, 9020, 9022, 9040, 9050, 9070, 9120, 9140, 9150, 9160, 9170, 9180, 9190, 9200, 9210, 9220, 9240, 9250, 9280, 9290, 9300, 9310, 9320, 9330, 9350, 9360, 9380, 9400, 9410, 9440, 9460, 9470, 9480, 9490, 9500, 9520, 9530, 9550, 9560, 9570, 9630, 9650, 9660, 9670, 9700, 9730, 9740, 9760, 9770, 9780, 9810, 9812, 9820, 9840, 9842, 9850, 9860, 9870, 9880, 9890, 9920, 9940, 1RI0668, 1RI1400

Appendix B – List of removed bridge IDs after filtering

Removed because of structure is a culvert

180, 240, 630, 1060, 1290, 1620, 2630, 2930, 4390, 5210, 5430, 6010, 7150, 7160, 7170, 7180, 7440, 7560, 7640, 8030, 8060, 8070, 8080, 8110, 8140, 8142, 8150, 8160, 8190, 8430, 9610, 9620, 9980, 10250, 10260, 10920, 10980, 11440, 11660, 11990, 12240, 12360, 12365, 12370, 12390, 12470, 12480, 1RI1366, 1RIGTE2

Removed because of insufficient inspection records

1200, 1825,1870, 2002, 2505, 3075, 4440, 4755, 4765, 4995, 5775, 5782, 6430, 6790, 6980, 7930, 7950, 8300, 8770, 9262, 9380, 9755, 9960, 9970, 10380, 10430, 10450, 10470, 10990, 11410, 12300, 12440,

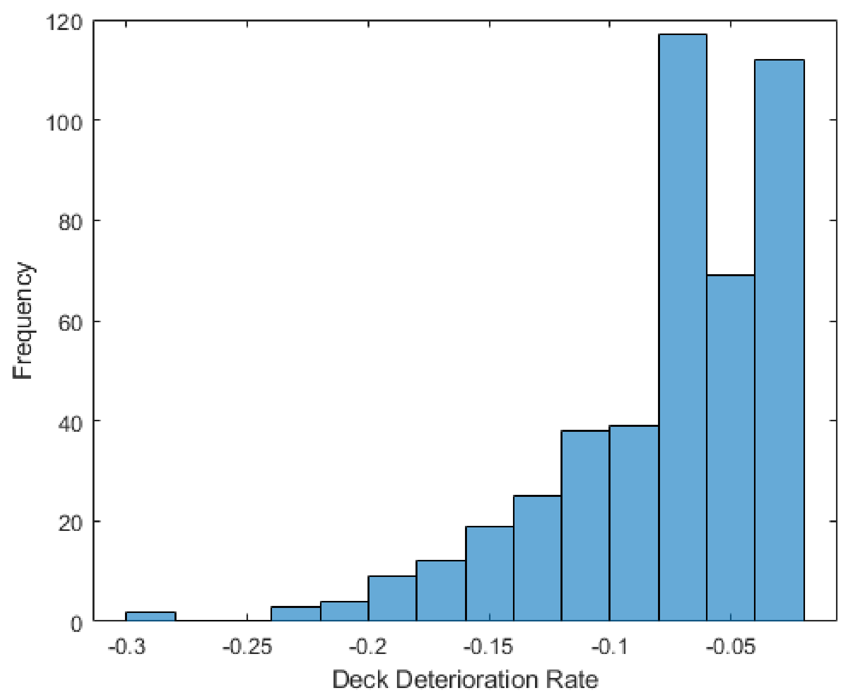
Removed because of invalid inspection intervals

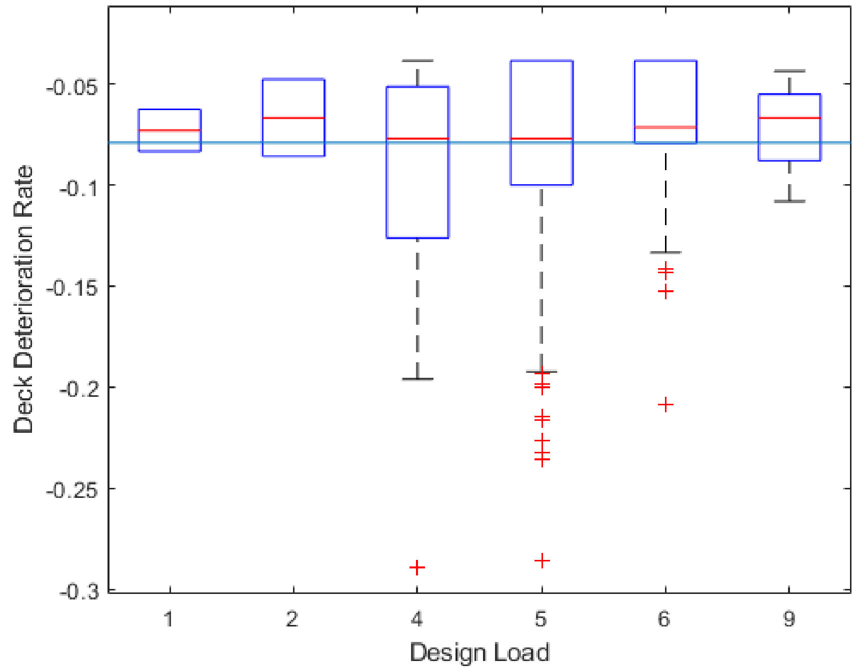
652, 3000, 3060, 4200, 5100, 6030, 6940, 8330, 8370, 8380, 8630, 8710, 8730, 8750, 9750, 9900, 9910, 9950

Removed because of missing and/or incredible data

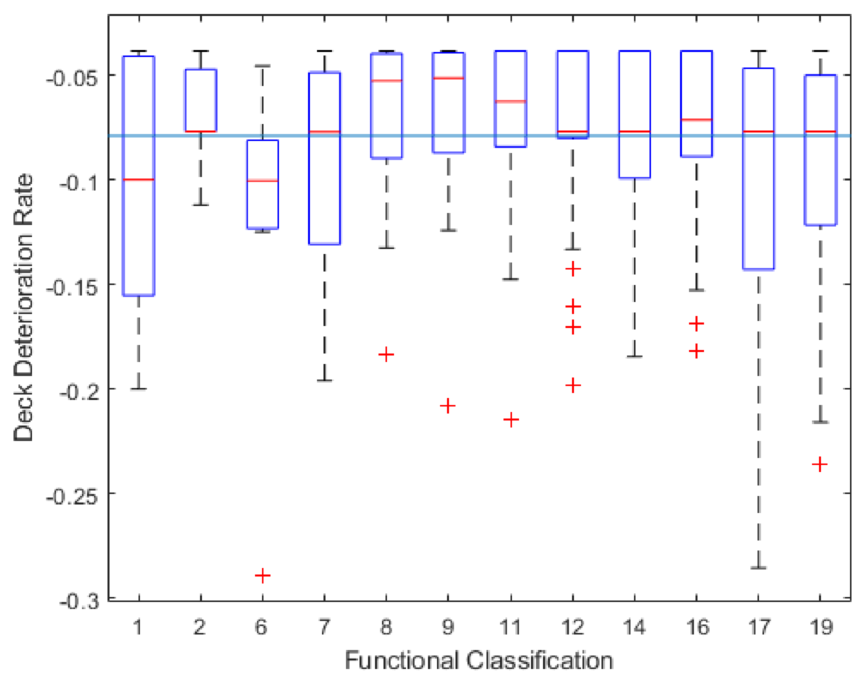
10, 20, 30, 70, 100, 140, 310, 340, 360, 380, 430, 440, 480, 520, 570, 590, 710, 810, 1000, 1050, 1080, 1083, 1110, 1230, 1240, 1340, 1350, 1420, 1460, 1480, 1580, 1590, 1740, 1780, 1880, 1900, 1950, 1960, 1980, 2000, 2060, 2080, 2190, 2270, 2420, 2440, 2450, 2460, 2500, 2640, 2690, 2710, 2730, 2750, 2790, 2880, 2910, 3030, 3040, 3050, 3062, 3150, 3280, 3504, 3510, 3530, 3590, 3670, 3730, 3780, 3810, 3840, 3880, 3900, 4240, 4310, 4340,4350, 4410, 4412, 4500, 4530, 4620, 4630, 4640, 4700, 4730, 4732, 4750, 4760, 4780, 47812, 4820, 4970, 5020, 5040, 5070, 5080, 5090, 5120, 5160, 5380, 5400, 5500, 5640, 5800, 6080, 6300, 6310, 6480, 6540, 6690, 6710, 6870, 7082, 7250, 7252, 7322, 7690, 7760, 7780, 7790, 7840, 7860, 7910, 7940, 8230, 8280, 8290, 8320, 8390, 8420, 8440, 8450, 8460, 8470, 8520, 8600, 8610, 8652, 8690, 8810, 8850, 8860, 8910, 8920, 9030, 9060, 9080, 9090, 9100, 9120, 9230, 9250, 9260, 9270, 9340, 9370, 9390, 9420, 9430, 9450, 9492, 9510, 9540, 9580, 9582, 9590, 9592, 9600, 9640, 9660, 9662, 9680, 9690, 9720, 9790, 9800, 9830, 9930, 10010, 10020, 10030, 10040, 10050, 10060, 10070, 10080, 10090, 10100, 10110, 10120, 10130, 10140, 10230, 10240, 10270, 10280, 10310, 10370, 10420, 10440, 10620, 10700, 10710, 10720, 10750, 10770, 10780, 10790, 10800, 10810, 10820, 10830, 10970, 11780, 11980, 12160, 12290, 15510, 1RI0669

Appendix C – Figures for bridge deck correlation analysis

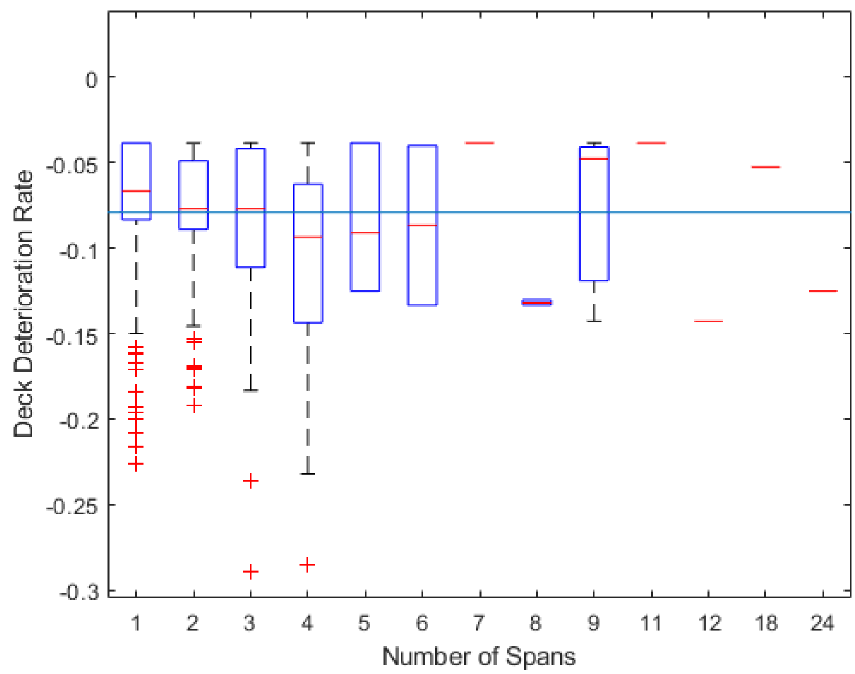


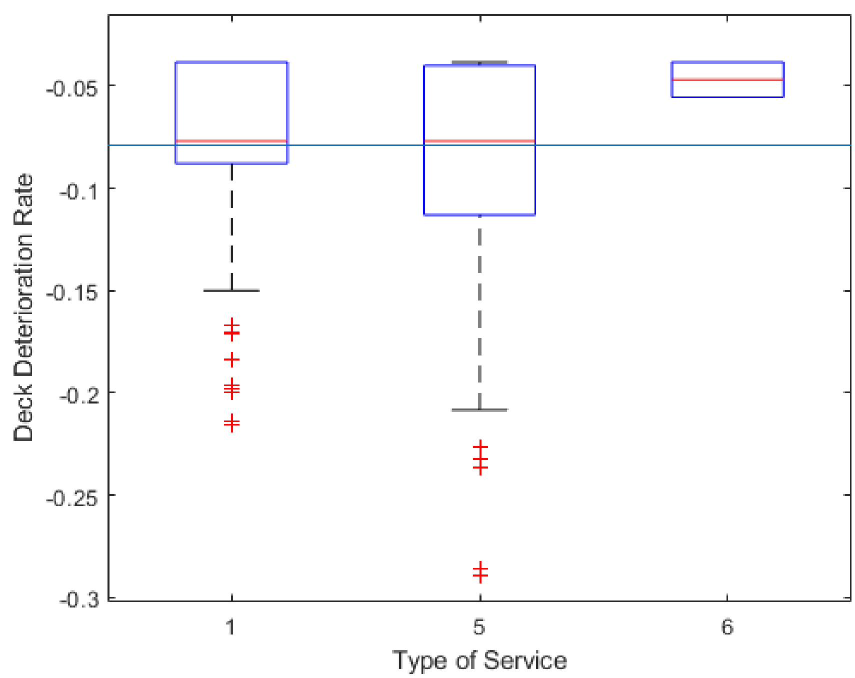


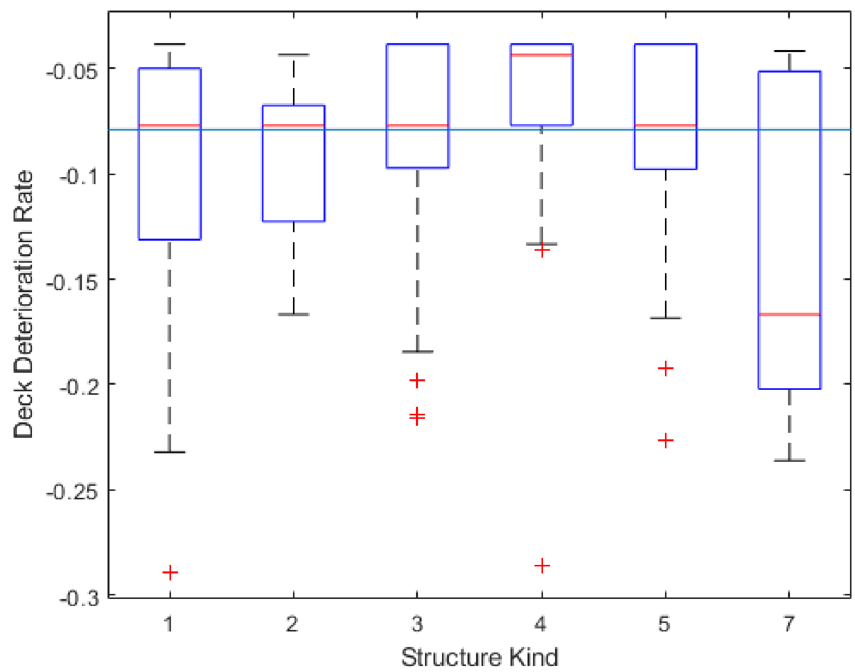
Deck Deterioration Rate
-0.05
-0.1
-0.15
-0.2
-0.25
-0.3
1 2 4 5 6 9
Design Load

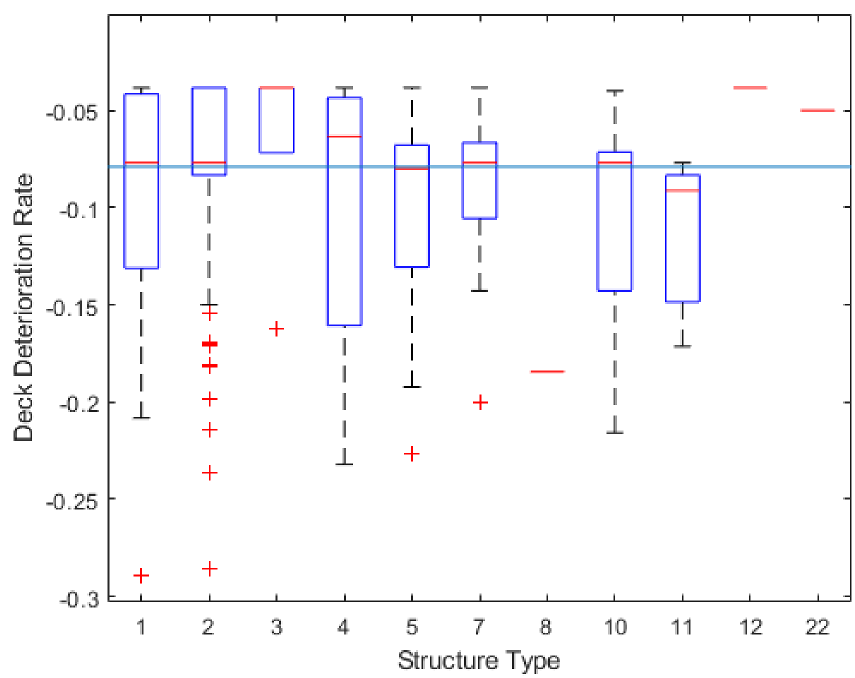


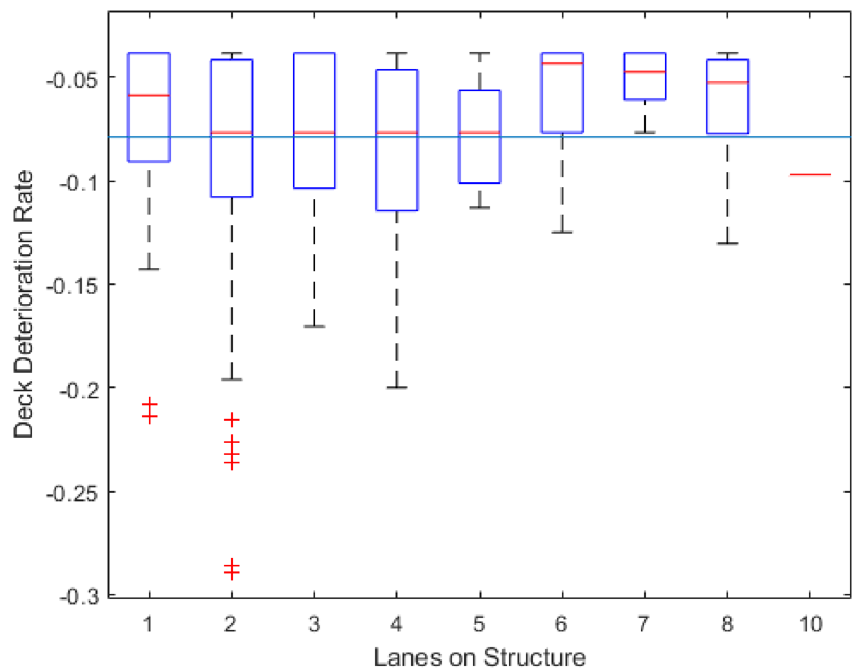
Deck Deterioration Rate
-0.05
-0.1
-0.15
-0.2
-0.25
-0.3
1 2 6 7 8 9 11 12 14 16 17 19
Functional Classification

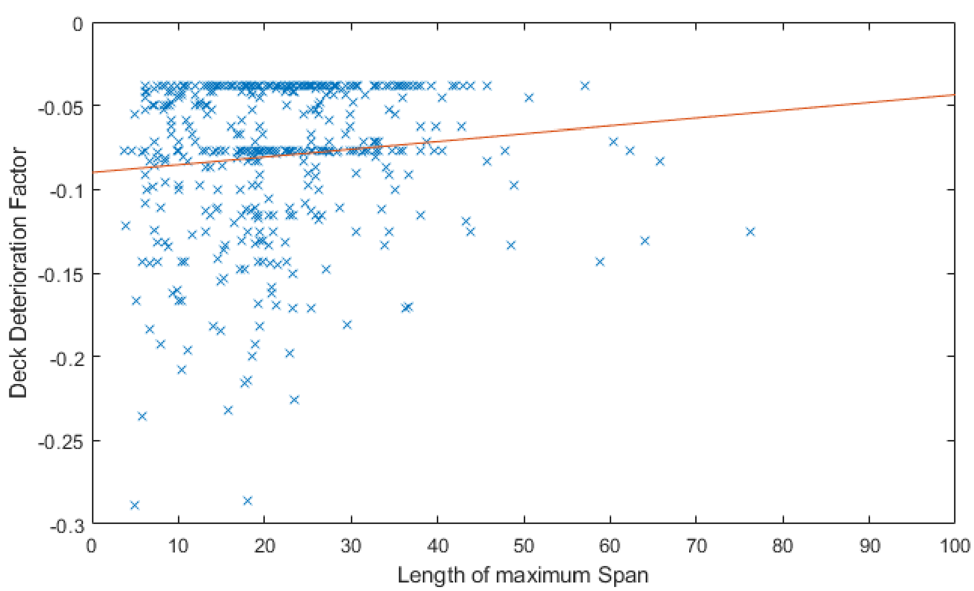

Deck Deterioration Rate
0
-0.05
-0.1
-0.15
-0.2
-0.25
-0.3
1
2
3
4
5
6
7
8
9
11
12
18
24
Number of Spans

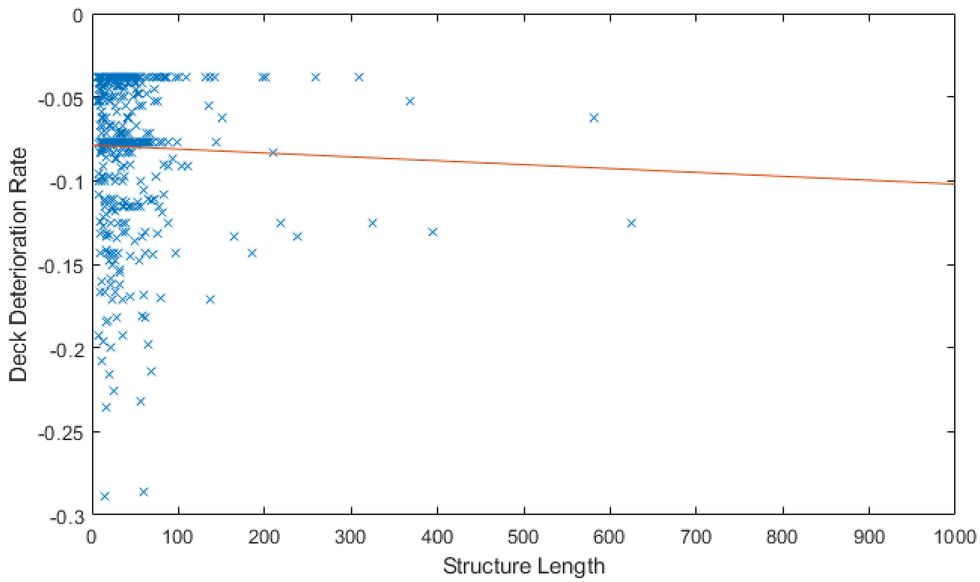

Deck Deterioration Rate
-0.05
-0.1
-0.15
-0.2
-0.25
-0.3
1
5
6
Type of Service

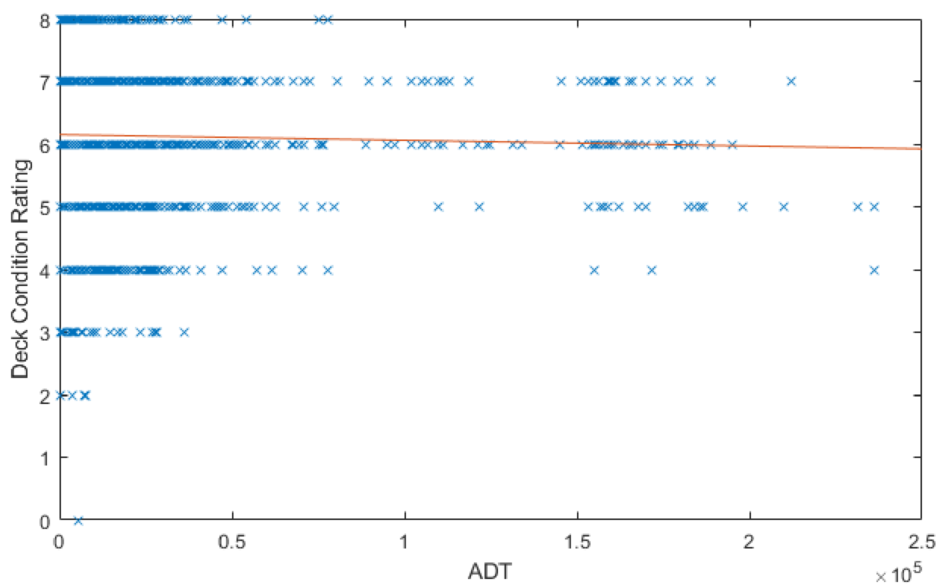

-0.05
-0.1
-0.15
-0.2
-0.25
-0.3
Deck Deterioration Rate
1
2
3
4
5
7
Structure Kind

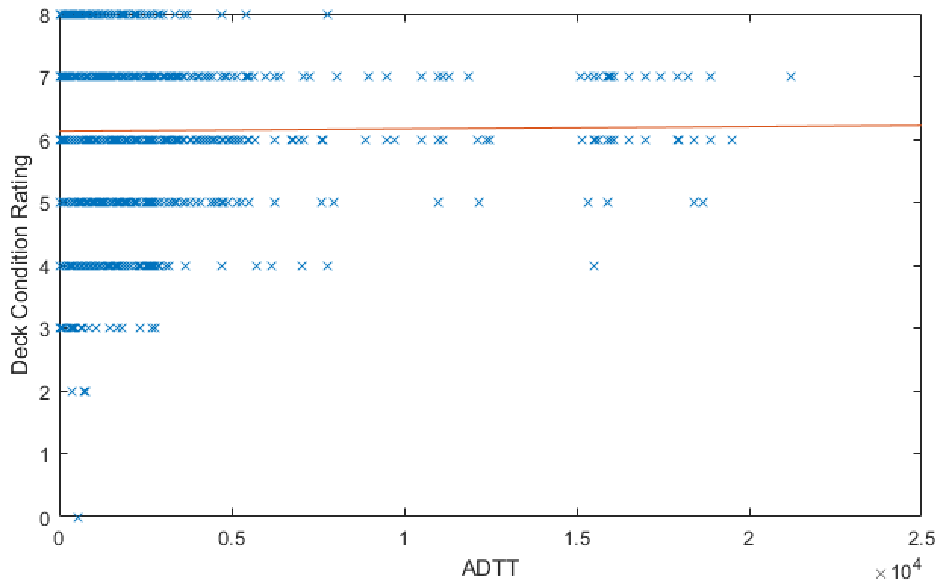

-0.05
-0.1
-0.15
-0.2
-0.25
-0.3
Deck Deterioration Rate
1
2
3
4
5
7
8
10
11
12
22
Structure Type


Deck Deterioration Rate
-0.05
-0.1
-0.15
-0.2
-0.25
-0.3
1
2
3
4
5
6
7
8
10
Lanes on Structure

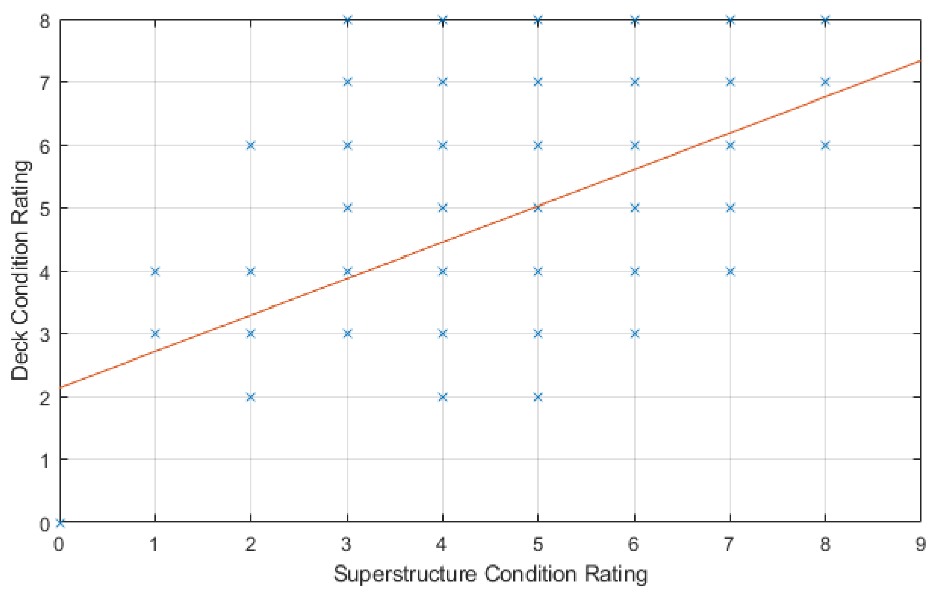

Deck Deterioration Factor
0
-0.05
-0.1
-0.15
-0.2
-0.25
-0.3
0
10
20
30
40
50
60
70
80
90
100
Length of maximum Span


Deck Deterioration Rate
Structure Length
0
-0.05
-0.1
-0.15
-0.2
-0.25
-0.3
0
100
200
300
400
500
600
700
800
900
1000

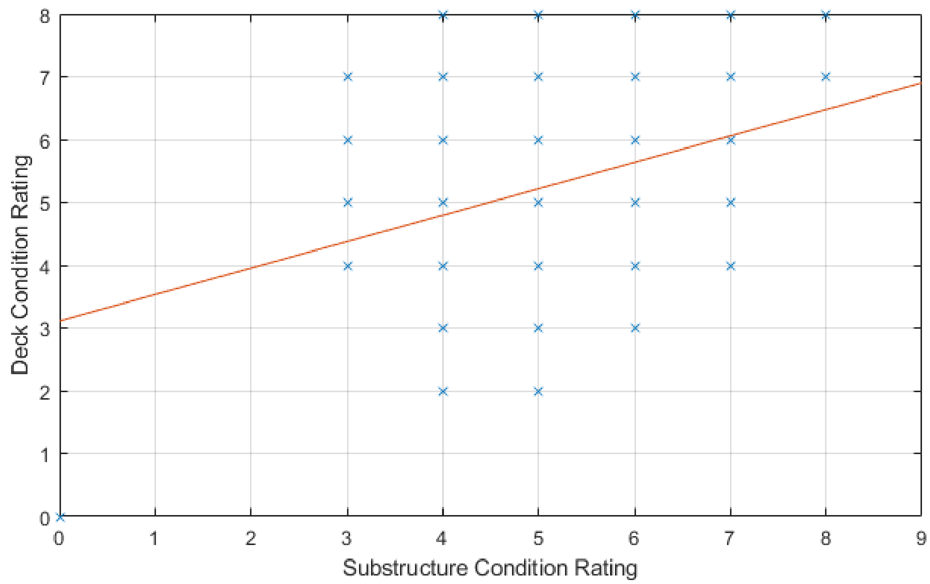

Deck Condition Rating
ADT
$\times 10^5$
8
7
6
5
4
3
2
1
0
0
0.5
1
1.5
2
2.5



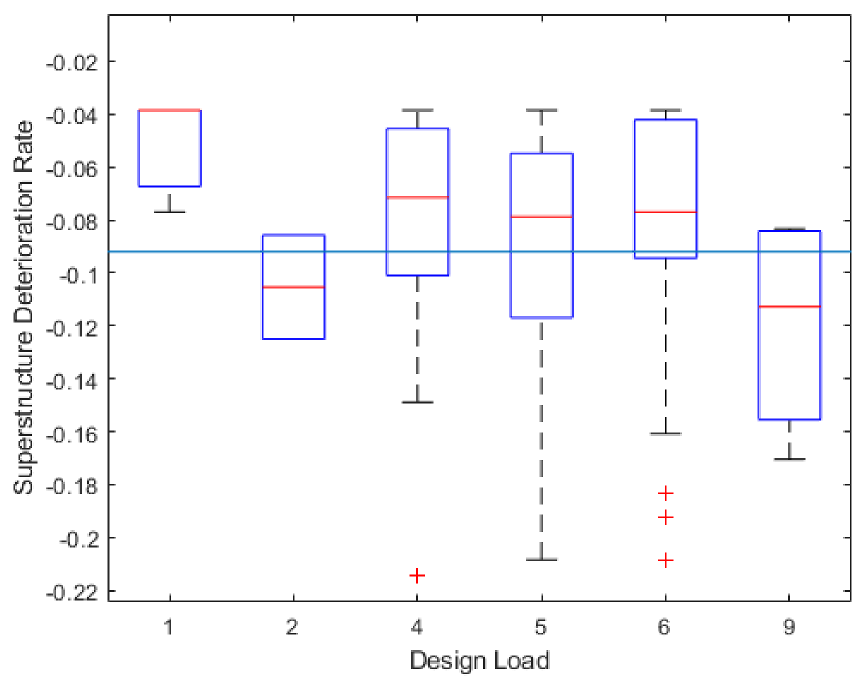
Deck Condition Rating
ADTT
$\times 10^4$

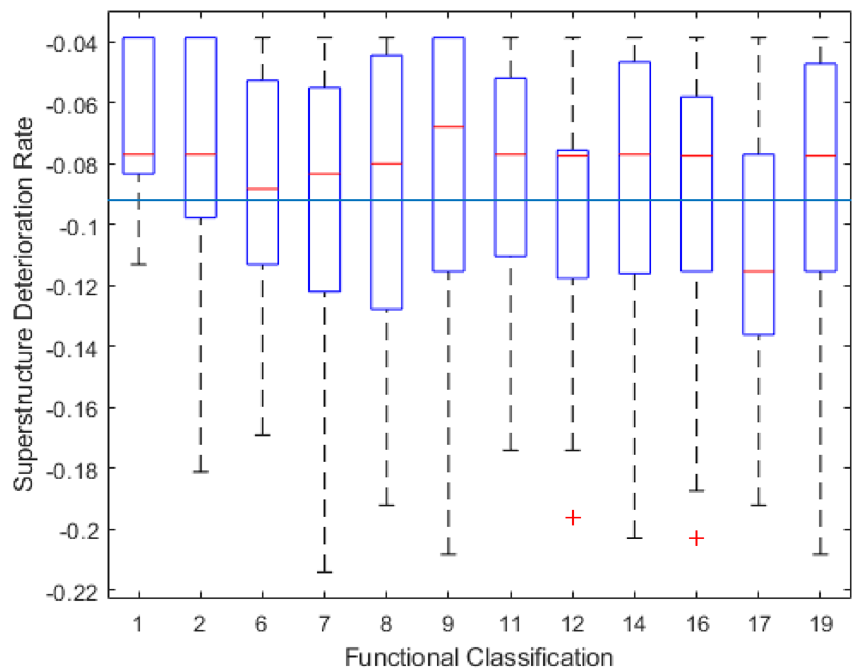


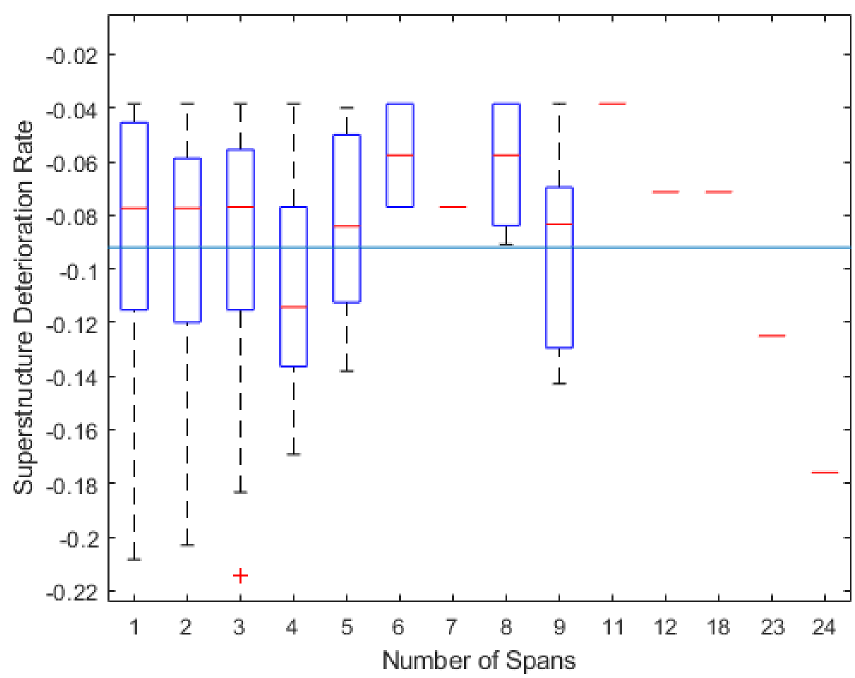
Deck Condition Rating
Superstructure Condition Rating

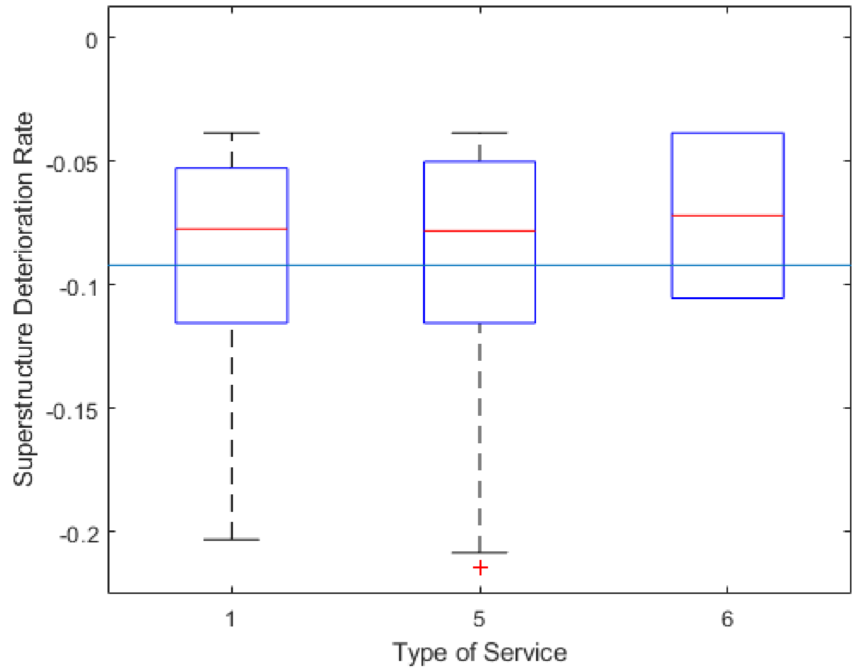


Appendix D – Figures for superstructure correlation analysis

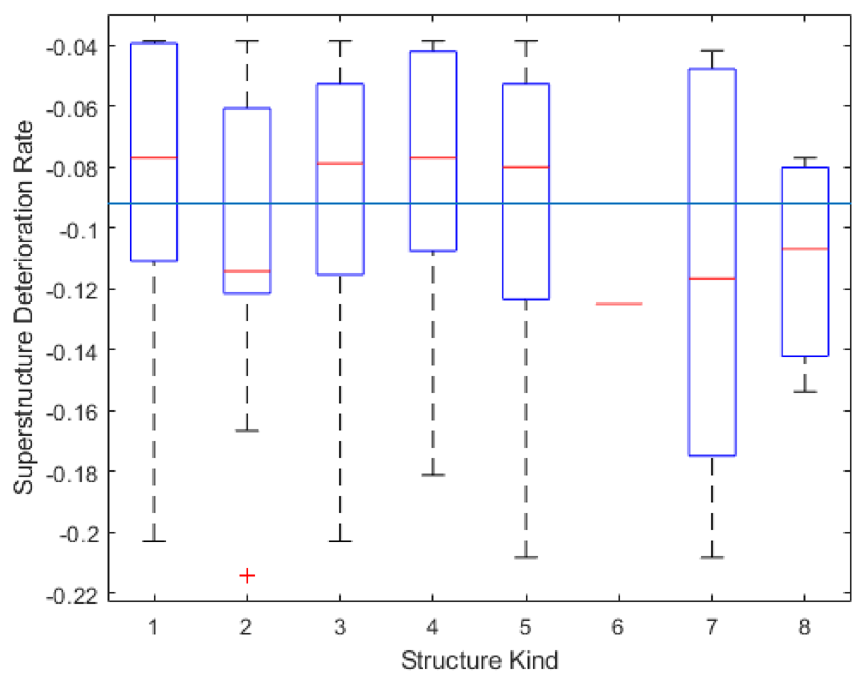



Superstructure Deterioration Rate
-0.04
-0.06
-0.08
-0.1
-0.12
-0.14
-0.16
-0.18
-0.2
-0.22
1 2 6 7 8 9 11 12 14 16 17 19
Functional Classification

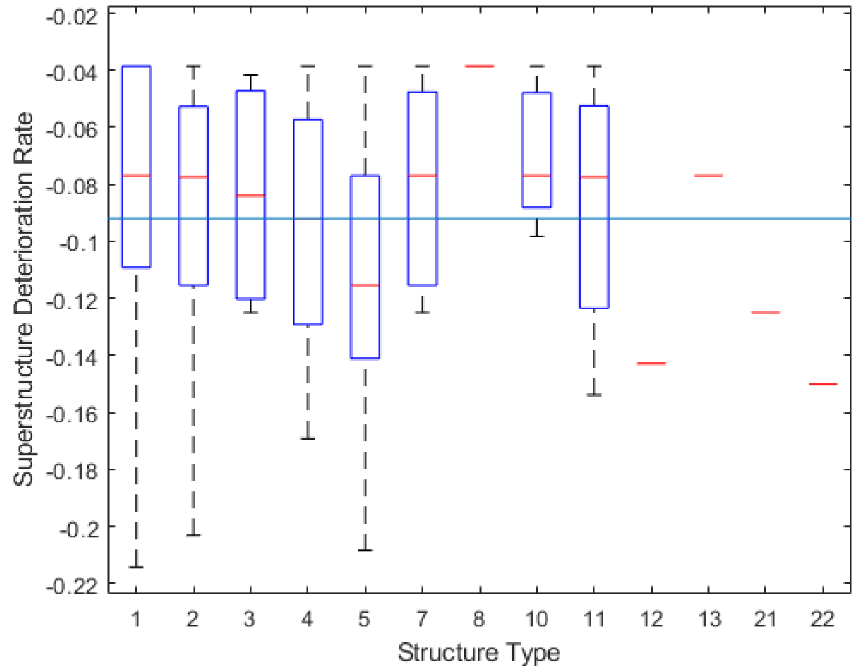

Superstructure Deterioration Rate
-0.02
-0.04
-0.06
-0.08
-0.1
-0.12
-0.14
-0.16
-0.18
-0.2
-0.22
1 2 3 4 5 6 7 8 9 11 12 18 23 24
Number of Spans



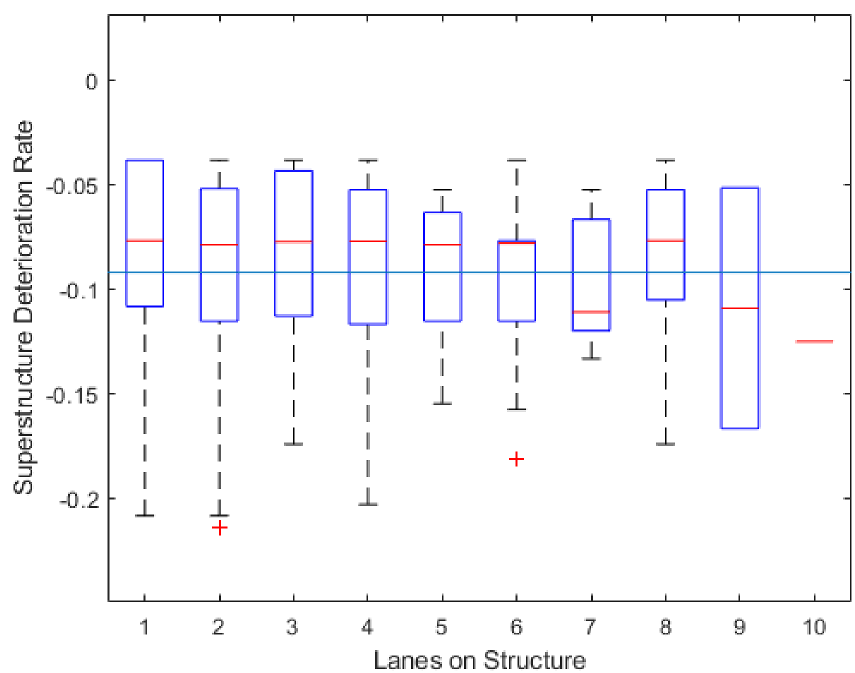
Superstructure Deterioration Rate
0
-0.05
-0.1
-0.15
-0.2
1
5
6
Type of Service



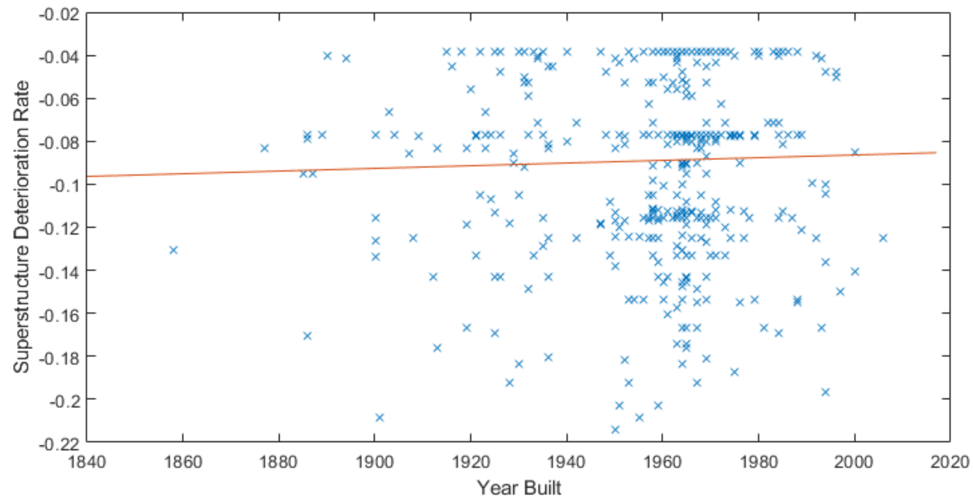
Superstructure Deterioration Rate
-0.04
-0.06
-0.08
-0.1
-0.12
-0.14
-0.16
-0.18
-0.2
-0.22
1
2
3
4
5
6
7
8
Structure Kind



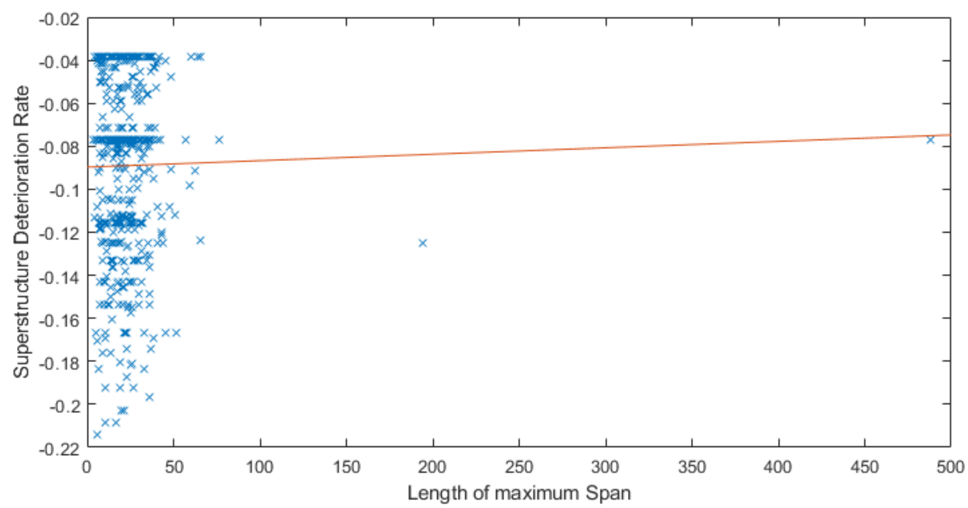
-0.02
-0.04
-0.06
-0.08
-0.1
-0.12
-0.14
-0.16
-0.18
-0.2
-0.22
Superstructure Deterioration Rate
1
2
3
4
5
7
8
10
11
12
13
21
22
Structure Type



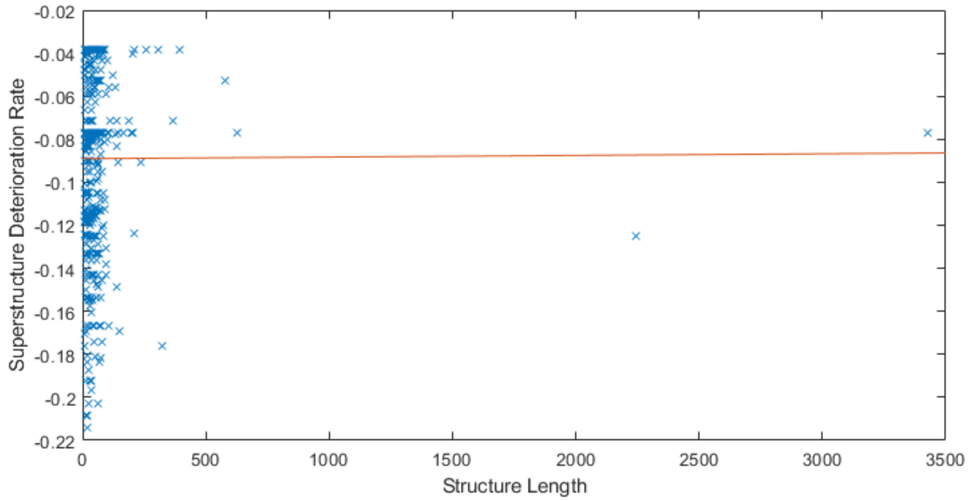
0
-0.05
-0.1
-0.15
-0.2
Superstructure Deterioration Rate
1
2
3
4
5
6
7
8
9
10
Lanes on Structure



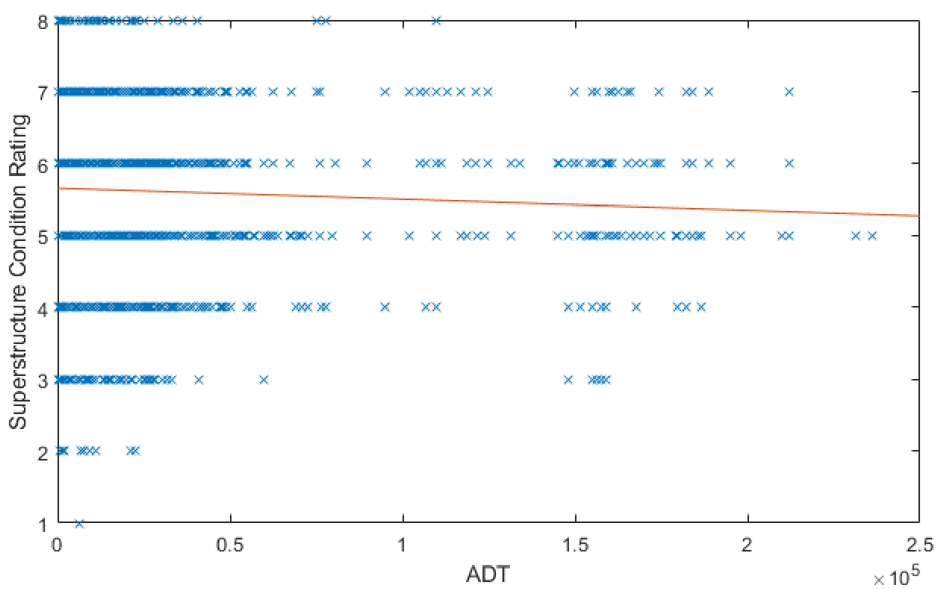
-0.02
-0.04
-0.06
-0.08
-0.1
-0.12
-0.14
-0.16
-0.18
-0.2
-0.22
Superstructure Deterioration Rate
1840
1860
1880
1900
1920
1940
1960
1980
2000
2020
Year Built



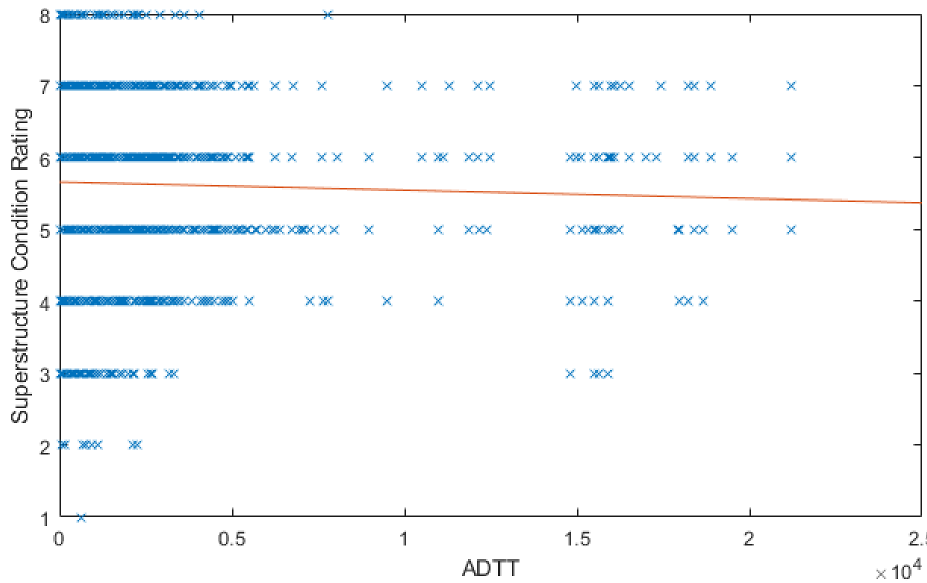
-0.02
-0.04
-0.06
-0.08
-0.1
-0.12
-0.14
-0.16
-0.18
-0.2
-0.22
Superstructure Deterioration Rate
0
50
100
150
200
250
300
350
400
450
500
Length of maximum Span



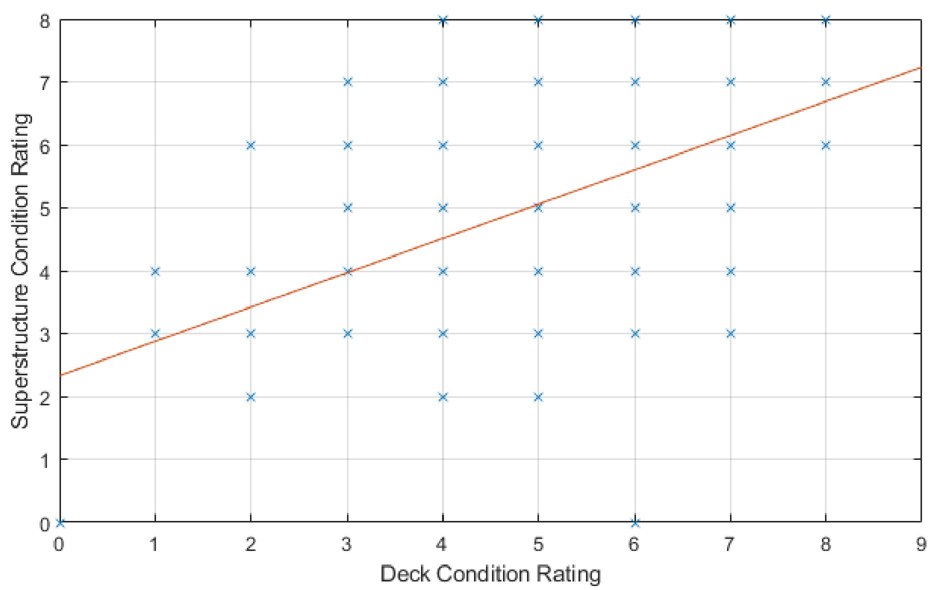
Superstructure Deterioration Rate
Structure Length
-0.02
-0.04
-0.06
-0.08
-0.1
-0.12
-0.14
-0.16
-0.18
-0.2
-0.22
0
500
1000
1500
2000
2500
3000
3500



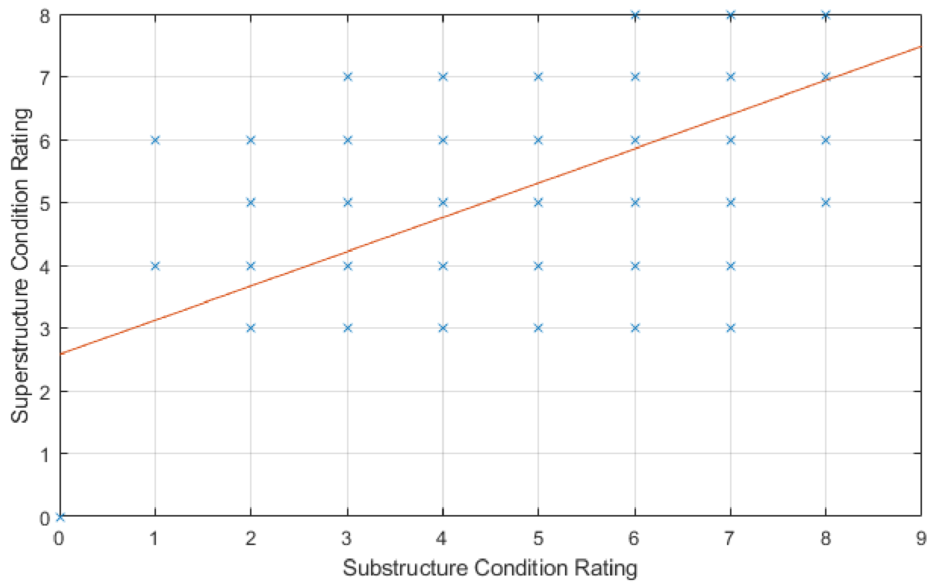
Superstructure Condition Rating
ADT
8
7
6
5
4
3
2
1
0
0.5
1
1.5
2
2.5
×10^5



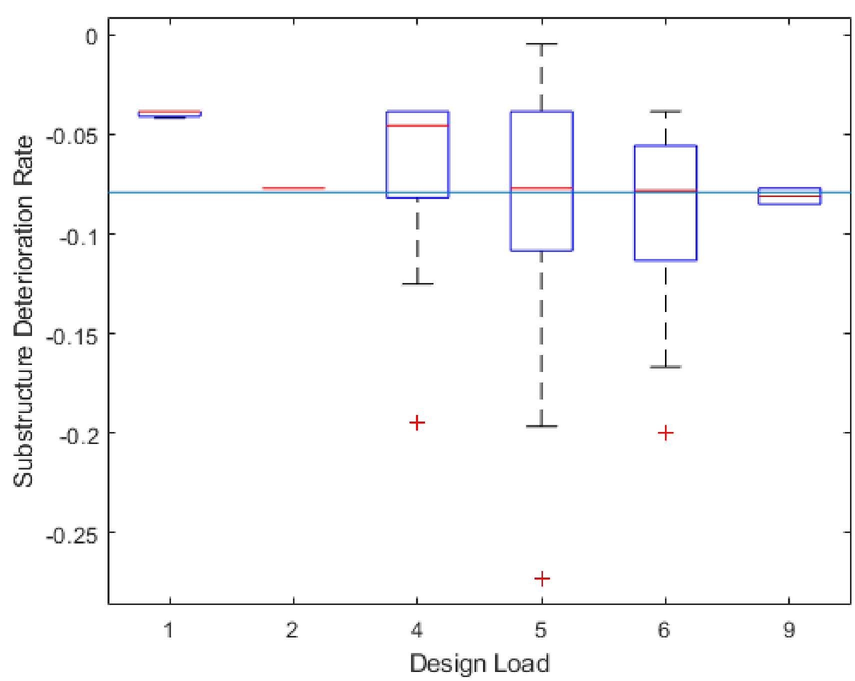
Superstructure Condition Rating
ADTT
× 10^4

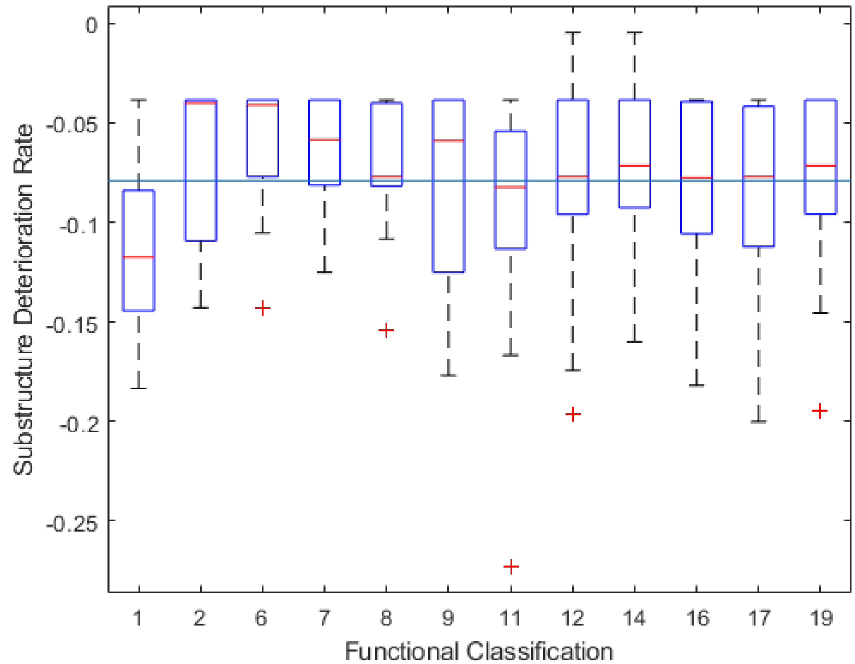


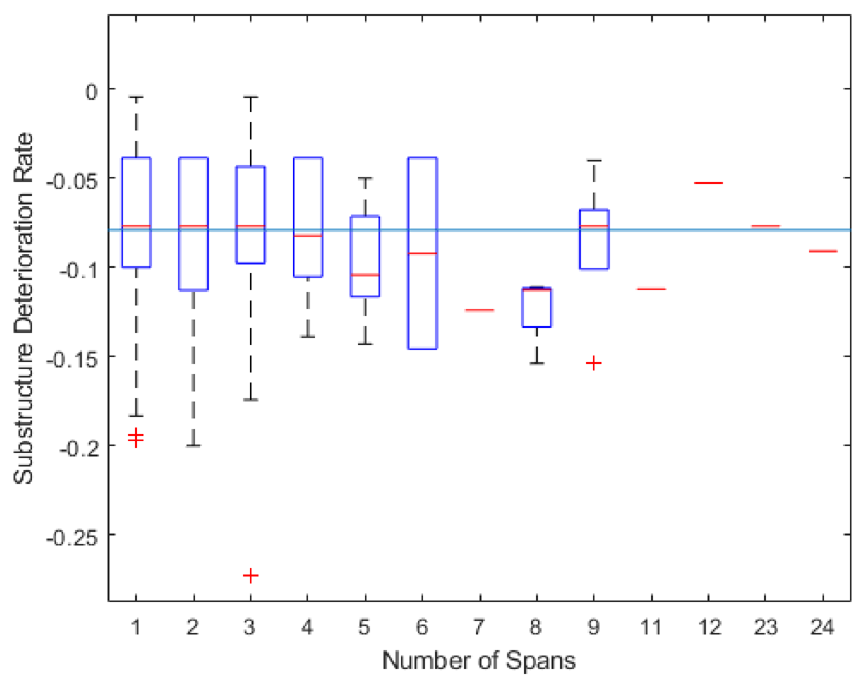
Superstructure Condition Rating
Deck Condition Rating

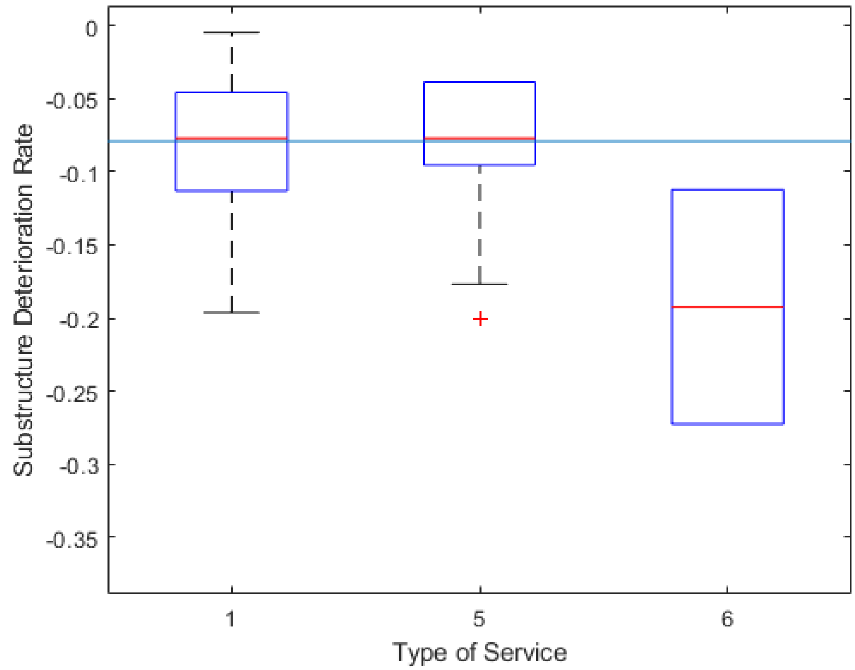


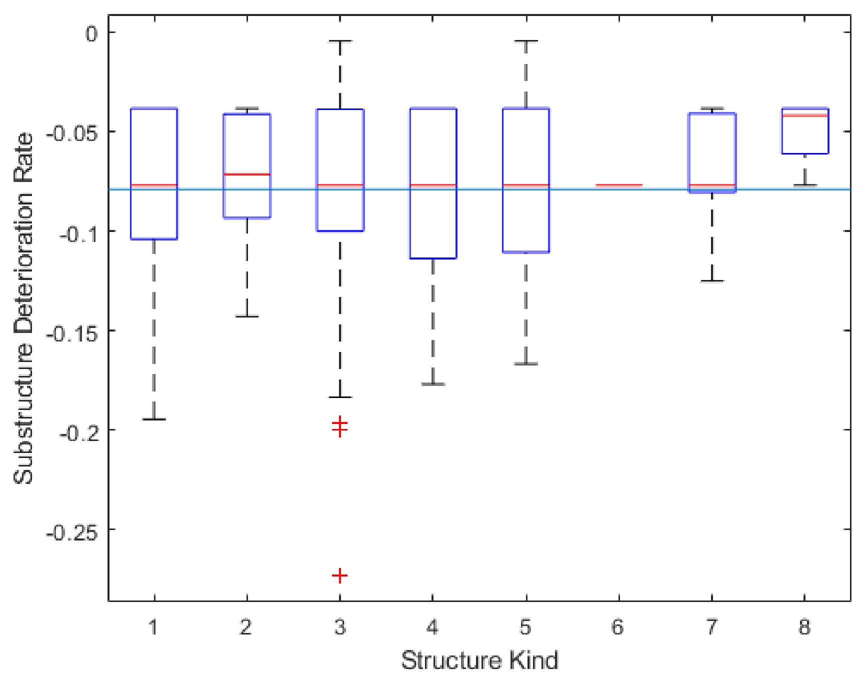
Appendix E – Figures for substructure correlation analysis

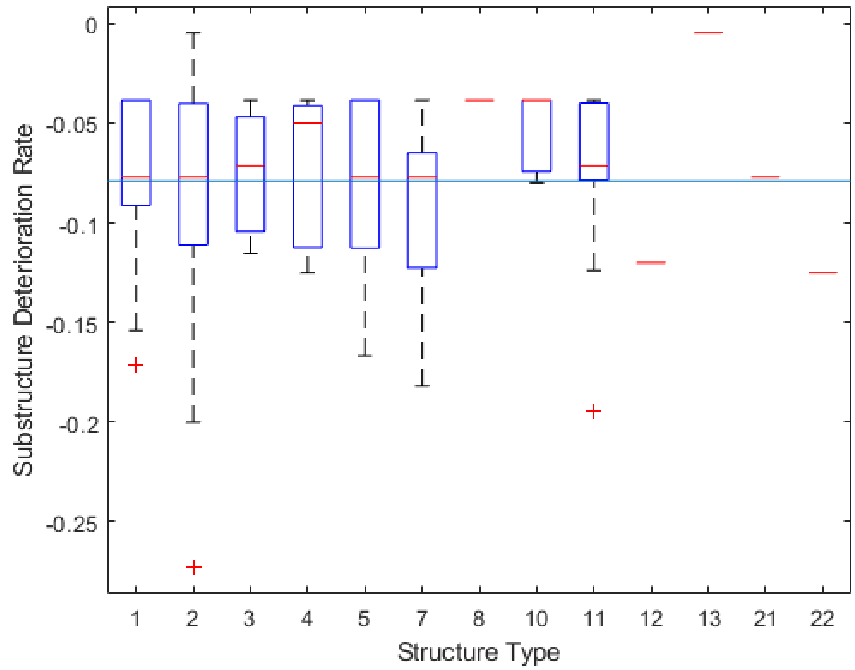



Substructure Deterioration Rate
0
-0.05
-0.1
-0.15
-0.2
-0.25
1 2 6 7 8 9 11 12 14 16 17 19
Functional Classification

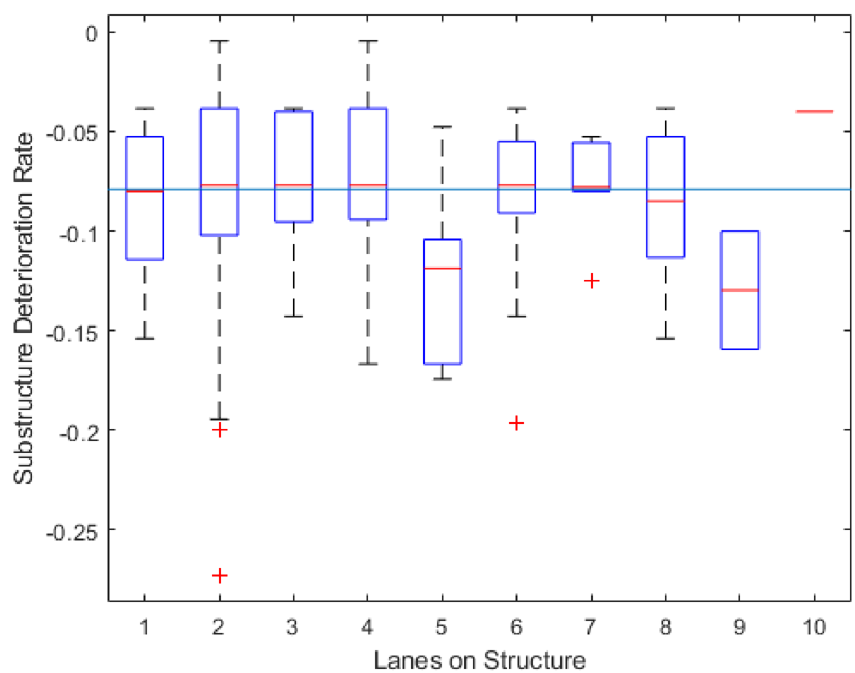

Substructure Deterioration Rate
0
-0.05
-0.1
-0.15
-0.2
-0.25
1 2 3 4 5 6 7 8 9 11 12 23 24
Number of Spans


0
-0.05
-0.1
-0.15
-0.2
-0.25
-0.3
-0.35
Substructure Deterioration Rate
1
5
6
Type of Service

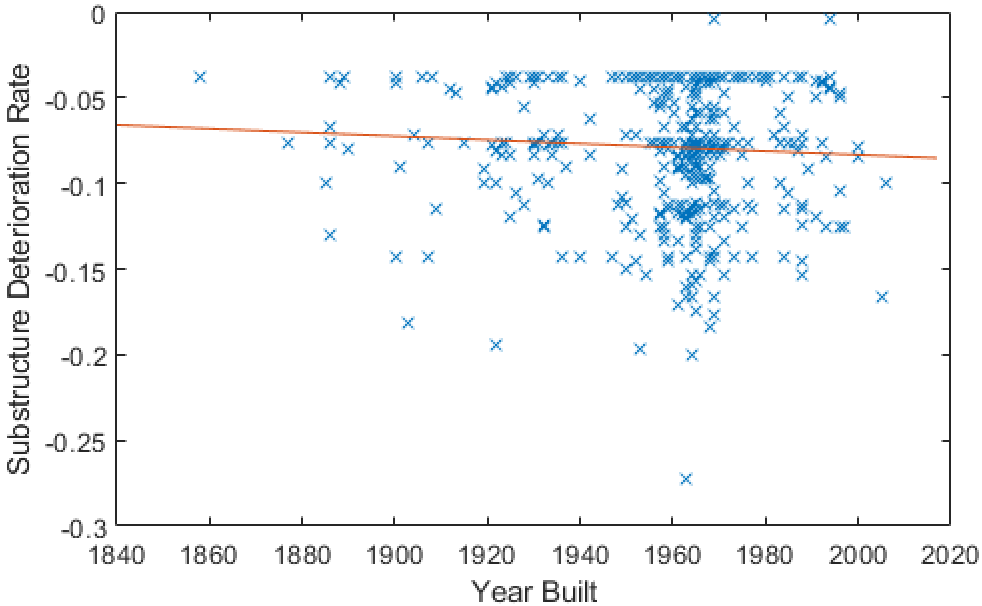

0
-0.05
-0.1
-0.15
-0.2
-0.25
Substructure Deterioration Rate
1
2
3
4
5
6
7
8
Structure Kind



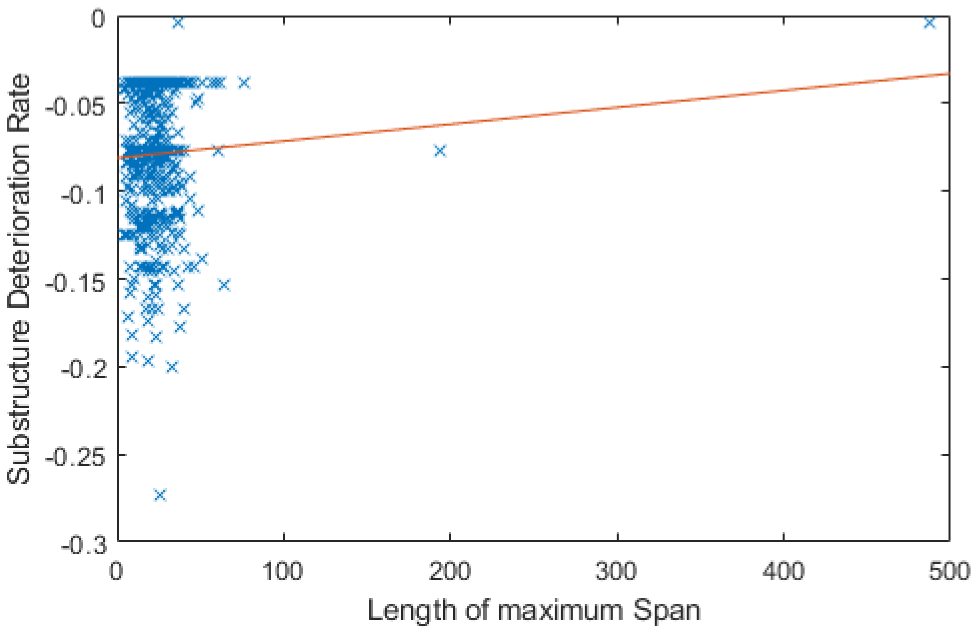
Substructure Deterioration Rate
0
-0.05
-0.1
-0.15
-0.2
-0.25
1 2 3 4 5 7 8 10 11 12 13 21 22
Structure Type



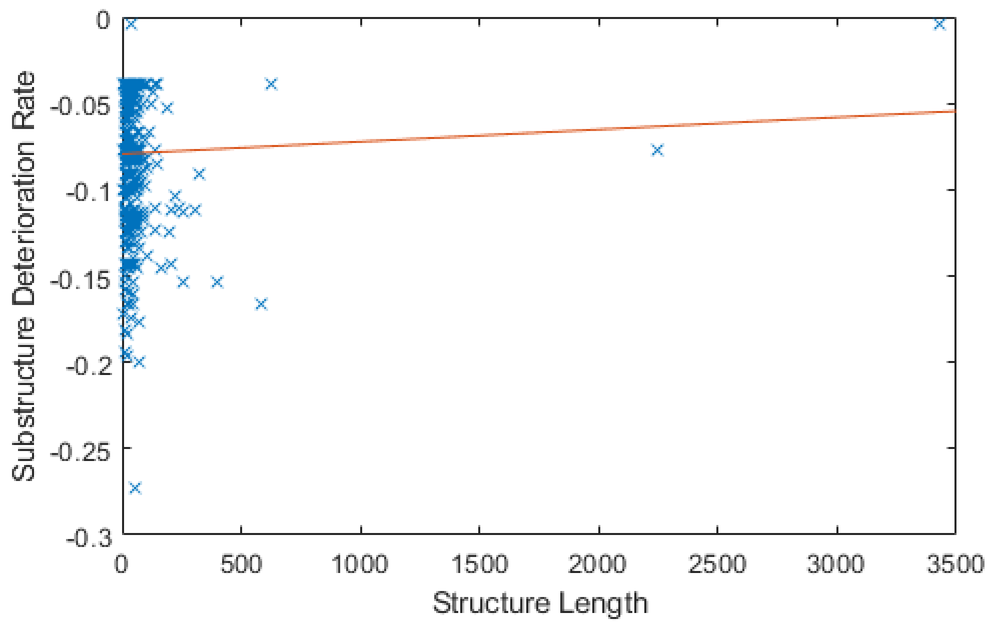
Substructure Deterioration Rate
0
-0.05
-0.1
-0.15
-0.2
-0.25
1 2 3 4 5 6 7 8 9 10
Lanes on Structure



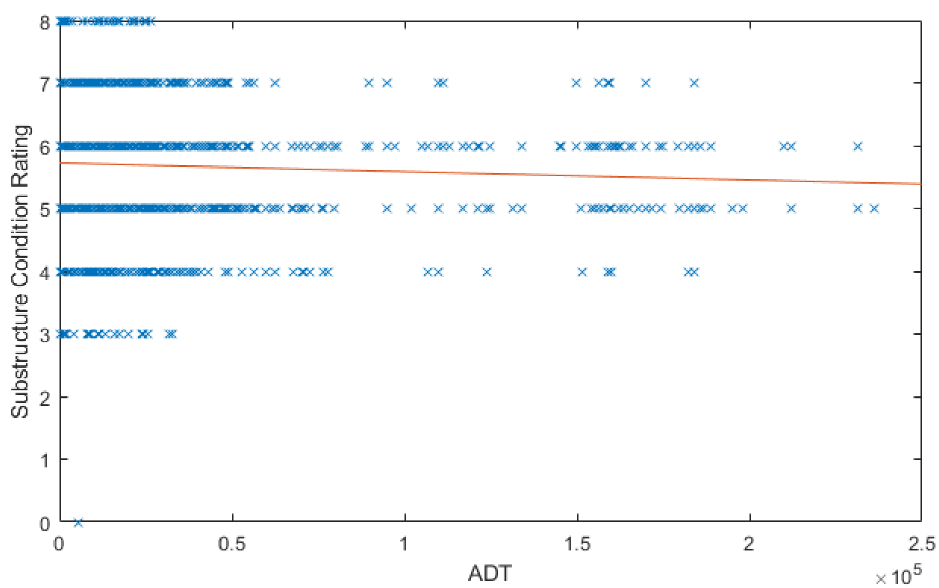
Substructure Deterioration Rate
0
-0.05
-0.1
-0.15
-0.2
-0.25
-0.3
1840 1860 1880 1900 1920 1940 1960 1980 2000 2020
Year Built



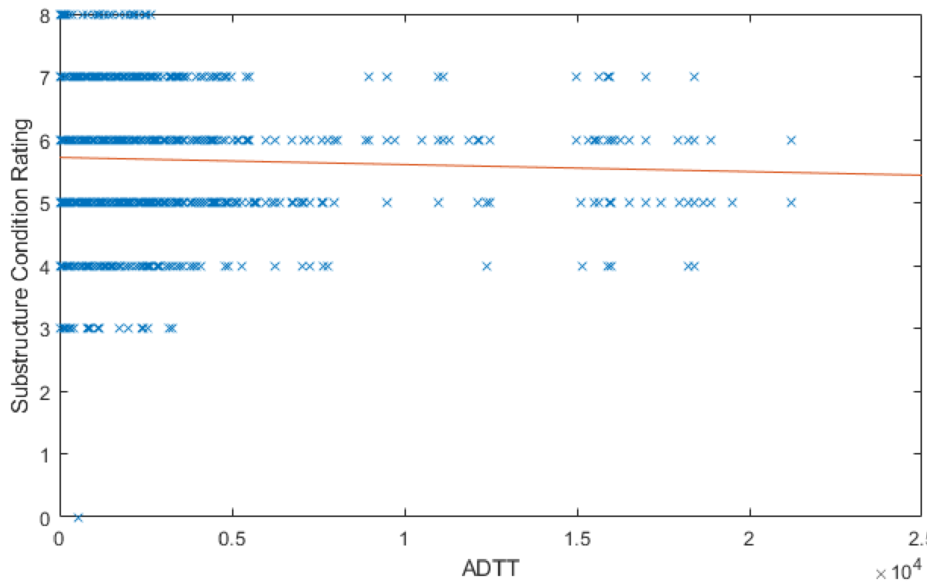
Substructure Deterioration Rate
0
-0.05
-0.1
-0.15
-0.2
-0.25
-0.3
0 100 200 300 400 500
Length of maximum Span



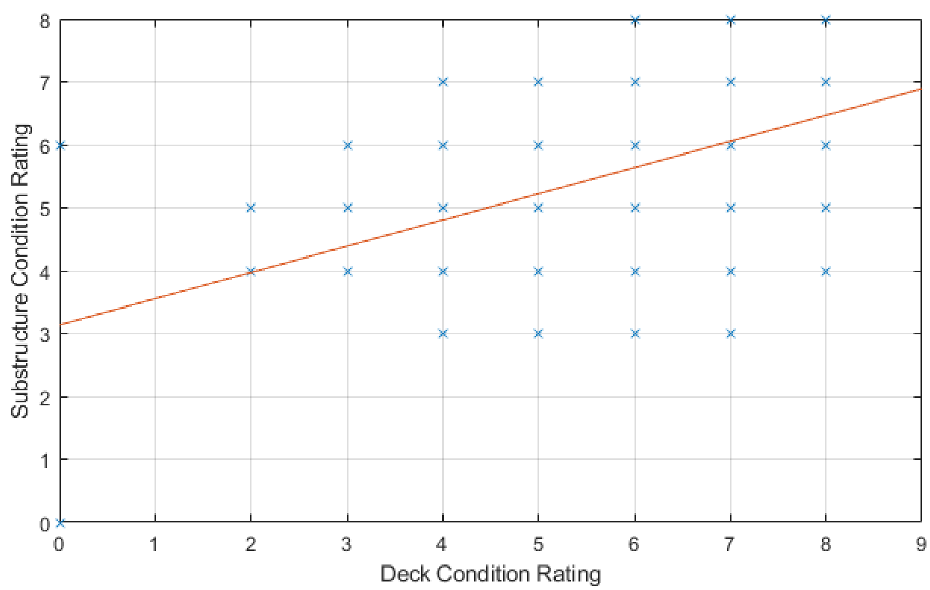
Substructure Deterioration Rate
Structure Length
0
-0.05
-0.1
-0.15
-0.2
-0.25
-0.3
0
500
1000
1500
2000
2500
3000
3500



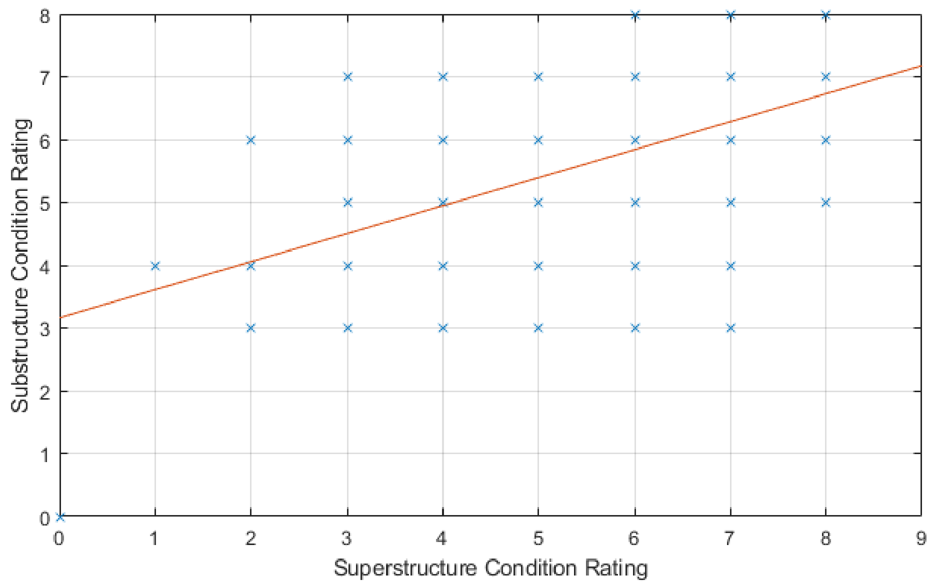
Substructure Condition Rating
ADT
$\times 10^5$
0
1
2
3
4
5
6
7
8
0
0.5
1
1.5
2
2.5



Substructure Condition Rating
ADTT
$\times 10^4$



Substructure Condition Rating
Deck Condition Rating



Appendix F – Marginal probabilities

	Lanes on Structure	Number of Spans	Structure Length	ADT	ADTT
Low	0.081315	0.520761	0.288927	0.283004	0.320238
Moderate	0.583045	0.204152	0.430796	0.347236	0.330042
High	0.33564	0.275087	0.280277	0.36976	0.349721

Appendix G – Conditional probability tables

Deck CPT for initial time slice

Structural Classification	Poor					
Loading Classification	Poor		Satisfactory		Good	
Maintenance	No	Yes	No	Yes	No	Yes
Poor	0.077832	0	0.093048	0	0.126722	0
Satisfactory	0.3836	0	0.464171	0	0.415978	0
Good	0.538568	1	0.442781	1	0.4573	1
Structural Classification	Satisfactory					
Loading Classification	Poor		Satisfactory		Good	
Maintenance	No	Yes	No	Yes	No	Yes
Poor	0.066363	0	0.052402	0	0.069056	0
Satisfactory	0.58156	0	0.505359	0	0.525485	0
Good	0.352077	1	0.442239	1	0.405459	1
Structural Classification	Good					
Loading Classification	Poor		Satisfactory		Good	
Maintenance	No	Yes	No	Yes	No	Yes
Poor	0.152778	0	0.032864	0	0.076806	0
Satisfactory	0.706019	0	0.60446	0	0.69532	0
Good	0.141204	1	0.362676	1	0.227874	1

Deck CPT for remaining time slices

Structural	Poor																	
Loading	Poor						Satisfactory						Good					
Previous Condition	Poor		Satisfactory		Good		Poor		Satisfactory		Good		Poor		Satisfactory		Good	
Maintenance	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Poor	1	0	0.046371	0	0	0	1	0	0.0199	0	0	0	1	0	0.042857	0	0	0
Satisfactory	0	0	0.953629	0	0.046832	0	0	0	0.9801	0	0.035897	0	0	0	0.957143	0	0.062112	0
Good	0	1	0	1	0.953168	1	0	1	0	1	0.964103	1	0	1	0	1	0.937888	1

Structural	Satisfactory																	
Loading	Poor						Satisfactory						Good					
Previous Condition	Poor		Satisfactory		Good		Poor		Satisfactory		Good		Poor		Satisfactory		Good	
Maintenance	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Poor	1	0	0.023652	0	0	0	1	0	0.018787	0	0	0	1	0	0.024749	0	0	0
Satisfactory	0	0	0.976348	0	0.086364	0	0	0	0.981213	0	0.067828	0	0	0	0.975251	0	0.078399	0
Good	0	1	0	1	0.913636	1	0	1	0	1	0.932172	1	0	1	0	1	0.921601	1

Structural	Good																	
Loading	Poor						Satisfactory						Good					
Previous Condition	Poor		Satisfactory		Good		Poor		Satisfactory		Good		Poor		Satisfactory		Good	
Maintenance	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Poor	1	0	0.034843	0	0	0	1	0	0.021413	0	0	0	1	0	0.021293	0	0	0
Satisfactory	0	0	0.965157	0	0.192982	0	0	0	0.978587	0	0.125828	0	0	0	0.978707	0	0.101176	0
Good	0	1	0	1	0.807018	1	0	1	0	1	0.874172	1	0	1	0	1	0.898824	1

Superstructure CPT for initial time slice

Structural Classification	Poor					
Loading Classification	Poor		Satisfactory		Good	
Maintenance	No	Yes	No	Yes	No	Yes
Poor	0.181877	0	0.165503	0	0.139303	0
Satisfactory	0.464725	0	0.585244	0	0.587065	0
Good	0.353398	1	0.249252	1	0.273632	1

Structural Classification	Satisfactory					
Loading Classification	Poor		Satisfactory		Good	
Maintenance	No	Yes	No	Yes	No	Yes
Poor	0.129435	0	0.108696	0	0.1277	0
Satisfactory	0.565217	0	0.647127	0	0.631194	0
Good	0.305347	1	0.244177	1	0.241105	1

Structural Classification	Good					
Loading Classification	Poor		Satisfactory		Good	
Maintenance	No	Yes	No	Yes	No	Yes
Poor	0.207289	0	0.10702	0	0.151561	0
Satisfactory	0.653759	0	0.665132	0	0.728097	0
Good	0.138952	1	0.227848	1	0.120342	1

Superstructure CPT for remaining time slices

Structural	Poor																	
Loading	Poor						Satisfactory						Good					
Previous Condition	Poor		Satisfactory		Good		Poor		Satisfactory		Good		Poor		Satisfactory		Good	
Maintenance	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Poor	1	0	0.043219	0	0	0	1	0	0.023381	0	0	0	1	0	0.04386	0	0	0
Satisfactory	0	0	0.956781	0	0.074219	0	0	0	0.976619	0	0.081633	0	0	0	0.95614	0	0.104762	0
Good	0	1	0	1	0.925781	1	0	1	0	1	0.918367	1	0	1	0	1	0.895238	1

Structural	Satisfactory																	
Loading	Poor						Satisfactory						Good					
Previous Condition	Poor		Satisfactory		Good		Poor		Satisfactory		Good		Poor		Satisfactory		Good	
Maintenance	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Poor	1	0	0.032319	0	0	0	1	0	0.028699	0	0	0	1	0	0.034865	0	0	0
Satisfactory	0	0	0.967681	0	0.087179	0	0	0	0.971301	0	0.130856	0	0	0	0.965135	0	0.133333	0
Good	0	1	0	1	0.912821	1	0	1	0	1	0.869144	1	0	1	0	1	0.866667	1

Structural	Good																	
Loading	Poor						Satisfactory						Good					
Previous Condition	Poor		Satisfactory		Good		Poor		Satisfactory		Good		Poor		Satisfactory		Good	
Maintenance	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Poor	1	0	0.043796	0	0	0	1	0	0.020755	0	0	0	1	0	0.033911	0	0	0
Satisfactory	0	0	0.956204	0	0.175439	0	0	0	0.979245	0	0.132979	0	0	0	0.966089	0	0.2	0
Good	0	1	0	1	0.824561	1	0	1	0	1	0.867021	1	0	1	0	1	0.8	1

Substructure CPT for initial time slice

Structural Classification	Poor					
Loading Classification	Poor		Satisfactory		Good	
Maintenance	No	Yes	No	Yes	No	Yes
Poor	0.10318	0	0.065803	0	0.017413	0
Satisfactory	0.532771	0	0.658026	0	0.728856	0
Good	0.364049	1	0.276171	1	0.253731	1
Structural Classification	Satisfactory					
Loading Classification	Poor		Satisfactory		Good	
Maintenance	No	Yes	No	Yes	No	Yes
Poor	0.123377	0	0.115981	0	0.082645	0
Satisfactory	0.586913	0	0.681536	0	0.698665	0
Good	0.28971	1	0.202483	1	0.21869	1
Structural Classification	Good					
Loading Classification	Poor		Satisfactory		Good	
Maintenance	No	Yes	No	Yes	No	Yes
Poor	0.218679	0	0.097814	0	0.142137	0
Satisfactory	0.646925	0	0.728423	0	0.749496	0
Good	0.134396	1	0.173763	1	0.108367	1

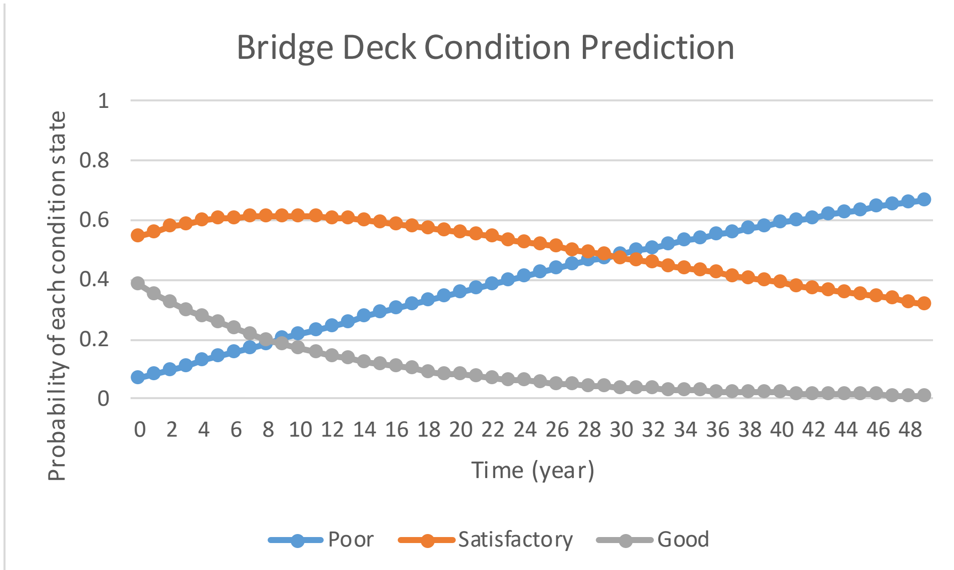
Substructure CPT for remaining time slices

Structural	Poor																	
Loading	Poor						Satisfactory						Good					
Previous Condition	Poor		Satisfactory		Good		Poor		Satisfactory		Good		Poor		Satisfactory		Good	
Maintenance	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Poor	1	0	0.02381	0	0	0	1	0	0.011182	0	0	0	1	0	0.014286	0	0	0
Satisfactory	0	0	0.97619	0	0.086142	0	0	0	0.988818	0	0.06367	0	0	0	0.985714	0	0.09901	0
Good	0	1	0	1	0.913858	1	0	1	0	1	0.93633	1	0	1	0	1	0.90099	1

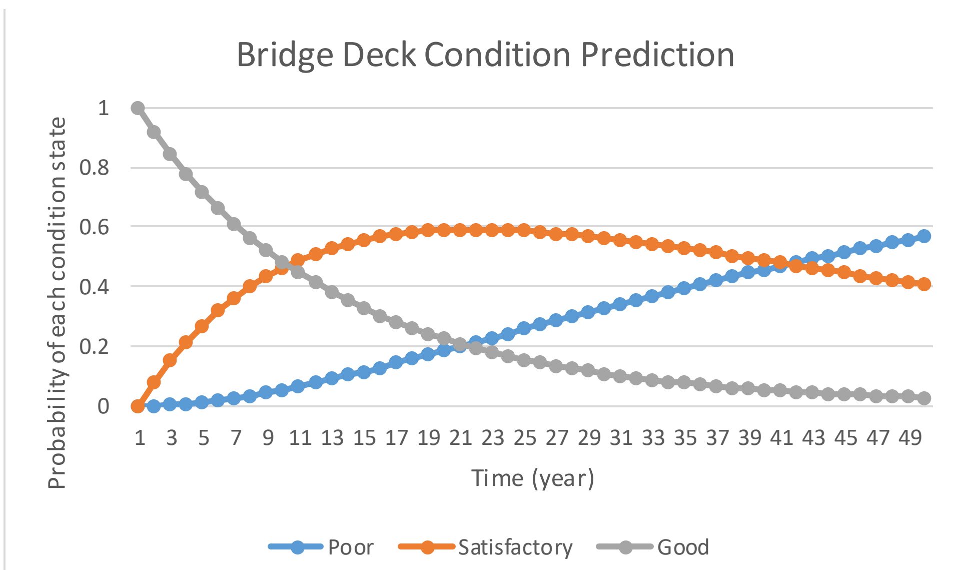
Structural	Satisfactory																	
Loading	Poor						Satisfactory						Good					
Previous Condition	Poor		Satisfactory		Good		Poor		Satisfactory		Good		Poor		Satisfactory		Good	
Maintenance	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Poor	1	0	0.026508	0	0	0	1	0	0.019976	0	0.003891	0	1	0	0.020535	0	0	0
Satisfactory	0	0	0.973492	0	0.085145	0	0	0	0.980024	0	0.136187	0	0	0	0.979465	0	0.120178	0
Good	0	1	0	1	0.914855	1	0	1	0	1	0.859922	1	0	1	0	1	0.879822	1

Structural	Good																	
Loading	Poor						Satisfactory						Good					
Previous Condition	Poor		Satisfactory		Good		Poor		Satisfactory		Good		Poor		Satisfactory		Good	
Maintenance	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Poor	1	0	0.055762	0	0	0	1	0	0.022109	0	0	0	1	0	0.030239	0	0	0
Satisfactory	0	0	0.944238	0	0.101695	0	0	0	0.977891	0	0.152778	0	0	0	0.969761	0	0.219048	0
Good	0	1	0	1	0.898305	1	0	1	0	1	0.847222	1	0	1	0	1	0.780952	1

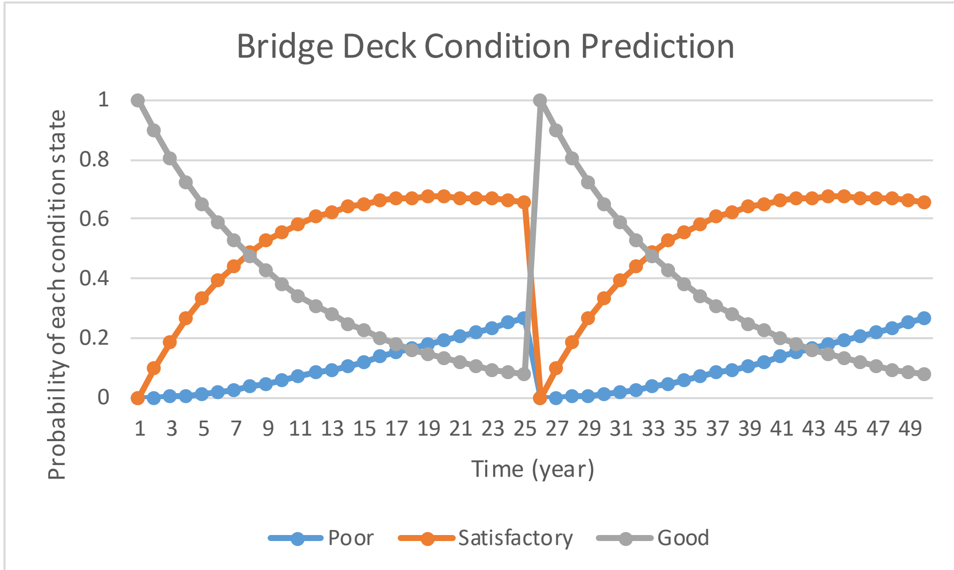
Appendix H – Figures for bridge element condition prediction



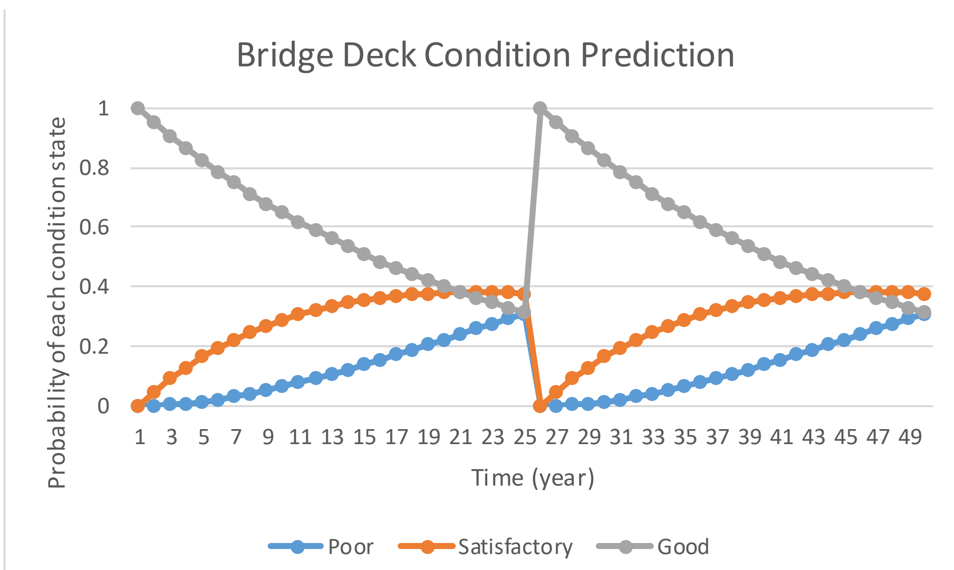
Bridge deck condition prediction – no parameters specified



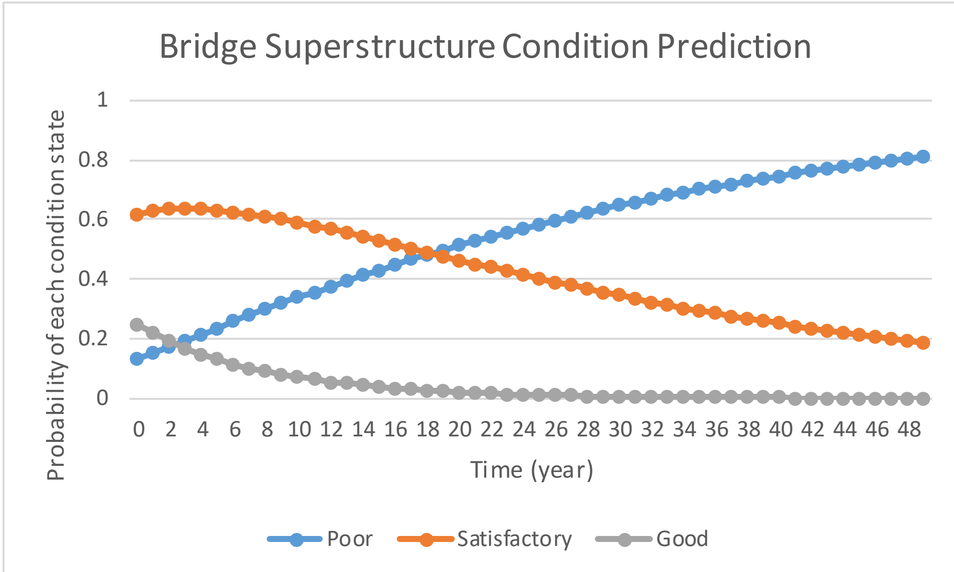
Bridge deck condition prediction – initial condition state of good



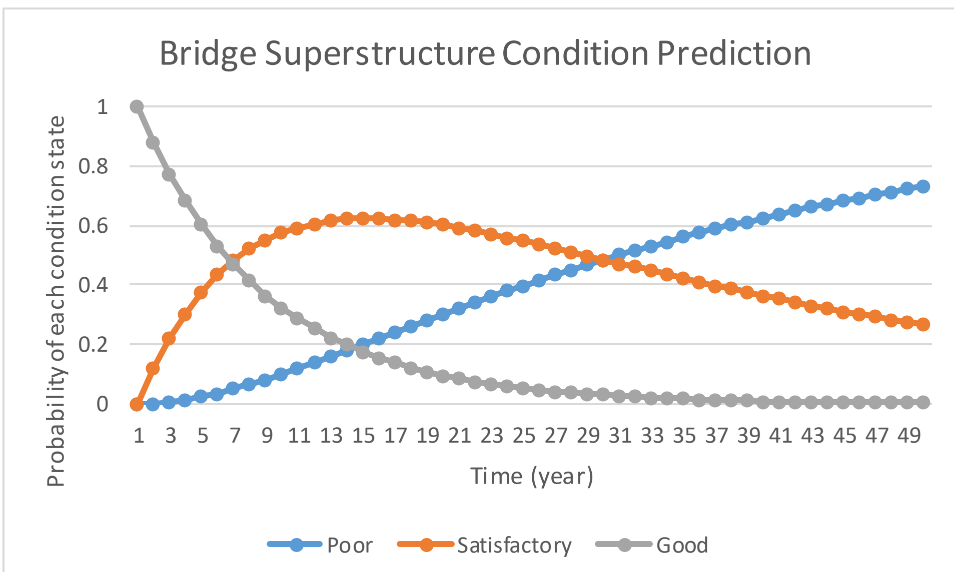
Bridge deck condition prediction – initial condition state of good, structural- and loading classification with a state of high, and a perfect maintenance action at year 25



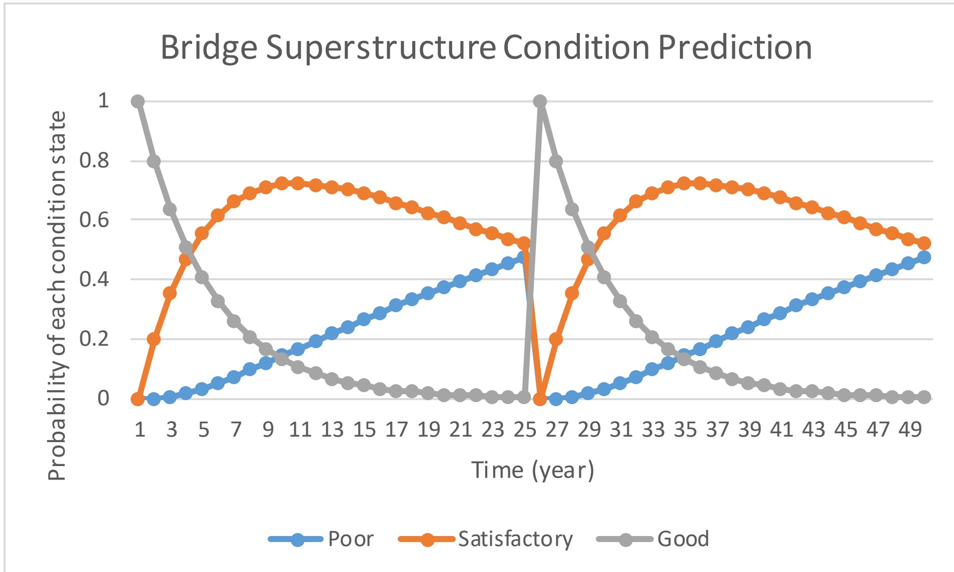
Bridge deck condition prediction – initial state of good, structural- and loading classification with a state of low, and a perfect maintenance action at year 25



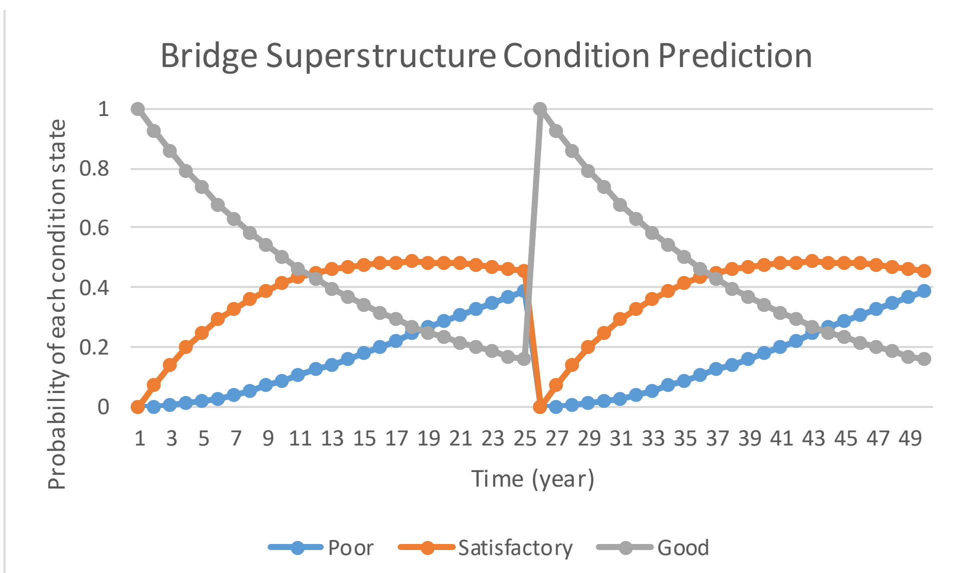
Bridge superstructure condition prediction – no parameters specified



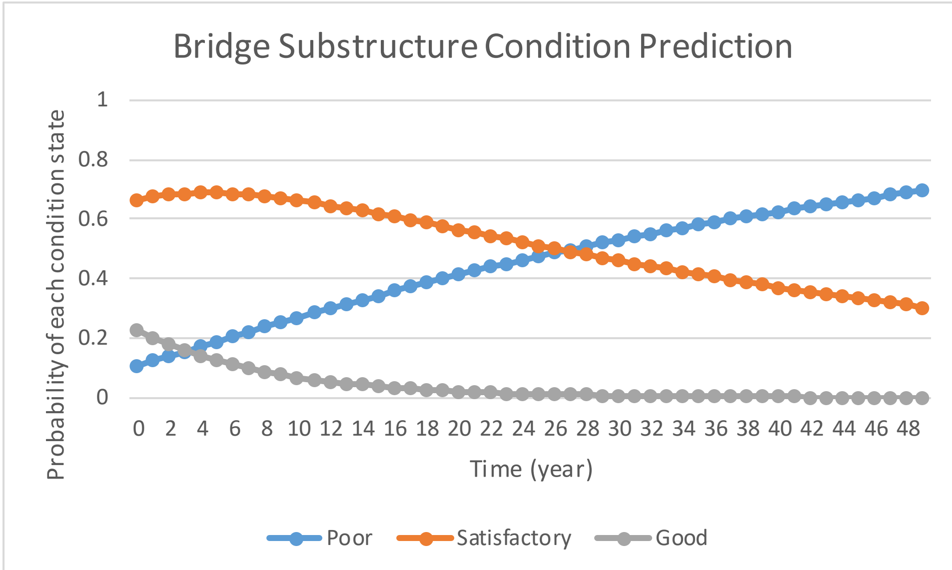
Bridge superstructure condition prediction – initial condition state of good



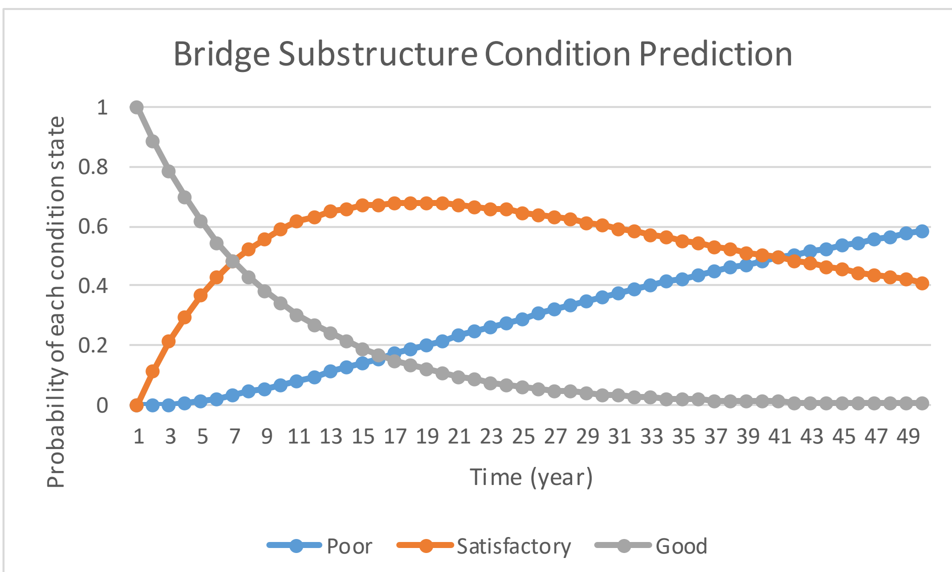
Bridge superstructure condition prediction – initial condition state of good, structural- and loading classification with a state of high, and a perfect maintenance action at year 25



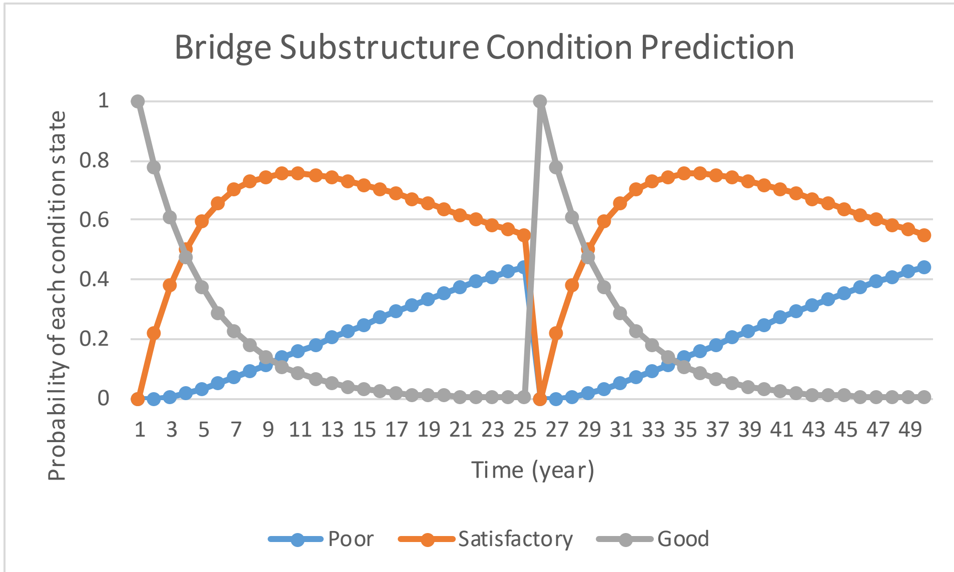
Bridge superstructure condition prediction – initial condition state of good, structural- and loading classification with a state of low, and a perfect maintenance action at year 25



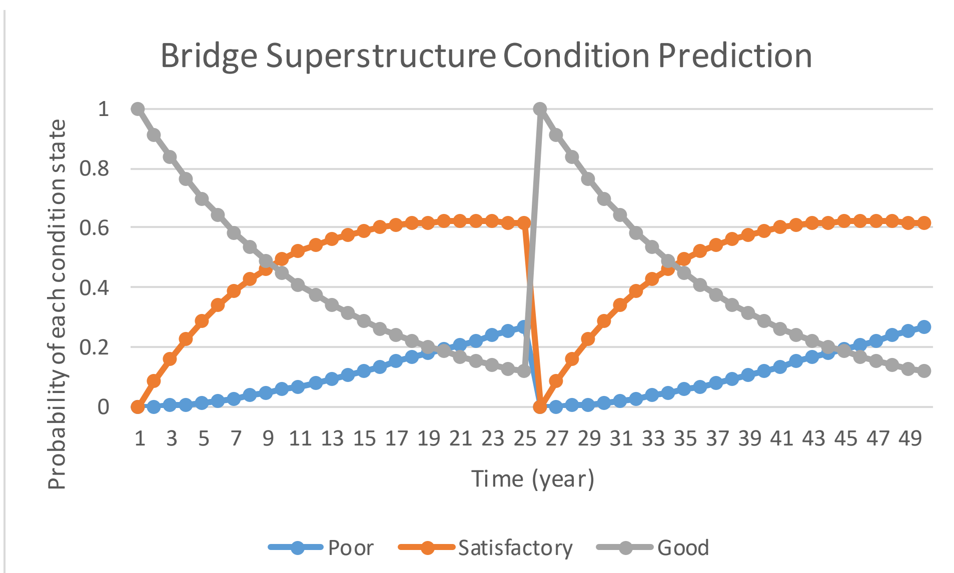
Bridge substructure condition prediction – no parameters specified



Bridge substructure condition prediction – initial condition state of good



Bridge substructure condition prediction – initial condition state of good, structural- and loading classification with a state of high, and a perfect maintenance action at year 25



Bridge substructure condition prediction – initial condition state of good, structural- and loading classification with a state of low, and a perfect maintenance action at year 25

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